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OCEANIC DATA ASSIMILATION TESTS WITH A ONE-DIMENSIONAL MODEL.(U)

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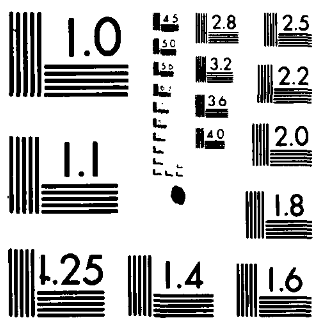

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THESIS

Oceanic Data Assimilation Tests
With a One-Dimensional Model

by

Dennis Glenn Larsen

December 1981

Thesis Advisor: R. L. Elsberry

REPORT DOCUMENTATION PAGE

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A data assimilation technique for incorporating relatively sparse ocean thermal structure profiles into the Garwood (1977) Oceanic Planetary Boundary Layer (OPBL) model is proposed. A summary of the data assimilation tests by Elsberry and Warrenfeltz (EW) is presented. The complete and perfect model generated verification data from the EW study were used to simulate incomplete and noisy data as might be expected in real data verifications. Random errors that are normally distributed

Block 19 Continued

Control group
Verification group
noisy control group
last of 15
average of 15
bathythermographic temperature profiles
climatology
persistence
data assimilation
root mean square errors

Block 20 Continued

about the mean mixed layer depth (MLD) and temperature (MLT), are added to subsets of the EW verification data during the summer and winter regimes. From these simulated tests, it was concluded that a data assimilation technique with a 1-D OPBL model can improve predictions of the ocean thermal structure even with incomplete and noisy verification data.
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Oceanic Data Assimilation Tests
With a One-Dimensional Model

by

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Submitted in partial fulfillment of the
requirements for the degree of

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ABSTRACT

A data assimilation technique for incorporating relatively sparse ocean thermal structure profiles into the Garwood (1977) Oceanic Planetary Boundary Layer (OPBL) model is proposed. A summary of the data assimilation tests by Elsberry and Warrenfeltz (EW) is presented. The complete and perfect model generated verification data from the EW study were used to simulate incomplete and noisy data as might be expected in real data verifications. Random errors that are normally distributed about the mean mixed layer depth (MLD) and temperature (MLT), are added to subsets of the EW verification data during the summer and winter regimes. From these simulated tests, it was concluded that a data assimilation technique with a 1-D OPBL model can improve predictions of the ocean thermal structure even with incomplete and noisy verification data.

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The author wishes to express sincere gratitude to Professor Russell L. Elsberry of the Naval Postgraduate School for his guidance and support throughout the research and preparation of this thesis.

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I. INTRODUCTION

A. THE UPPER 200 M OCEANIC THERMAL STRUCTURE

The need to predict the thermal structure in the upper 200 M of the ocean is ever increasing. With the growing problem of feeding the world's population, the accurate prediction of the ocean thermal structure will be of great value to the fishing industry. The U.S. Navy faces a rapidly growing, technically improved and potentially hostile submarine fleet. The accurate knowledge and prediction of the ocean mixed layer depth (MLD) is a must. Anti-submarine warfare (ASW) operations require a good estimate of the MLD which may greatly affect their passive and active sonar capabilities. Future research for the advancement of Meteorology must also include a better understanding of the upper ocean temperature structure. Models predicting hurricane development and movement are dependent upon the ocean surface or mixed layer temperature (MLT). Even some synoptic scale and mesoscale meterological events are considered to be influenced directly by the ocean interacting with the atmosphere. Therefore, a good understanding of the ocean thermal structure in the upper 200 M and the ability to predict it accurately are essential.

An idealized temperature profile for the upper 200 M of the ocean is shown in Figure 1. The top of this profile is represented by an isothermal layer of thickness h. This layer is made isothermal by the mixing due to the surface winds and the upward surface heat flux. It is often referred to as the Ocean Planetary Boundary Layer (OPBL). The

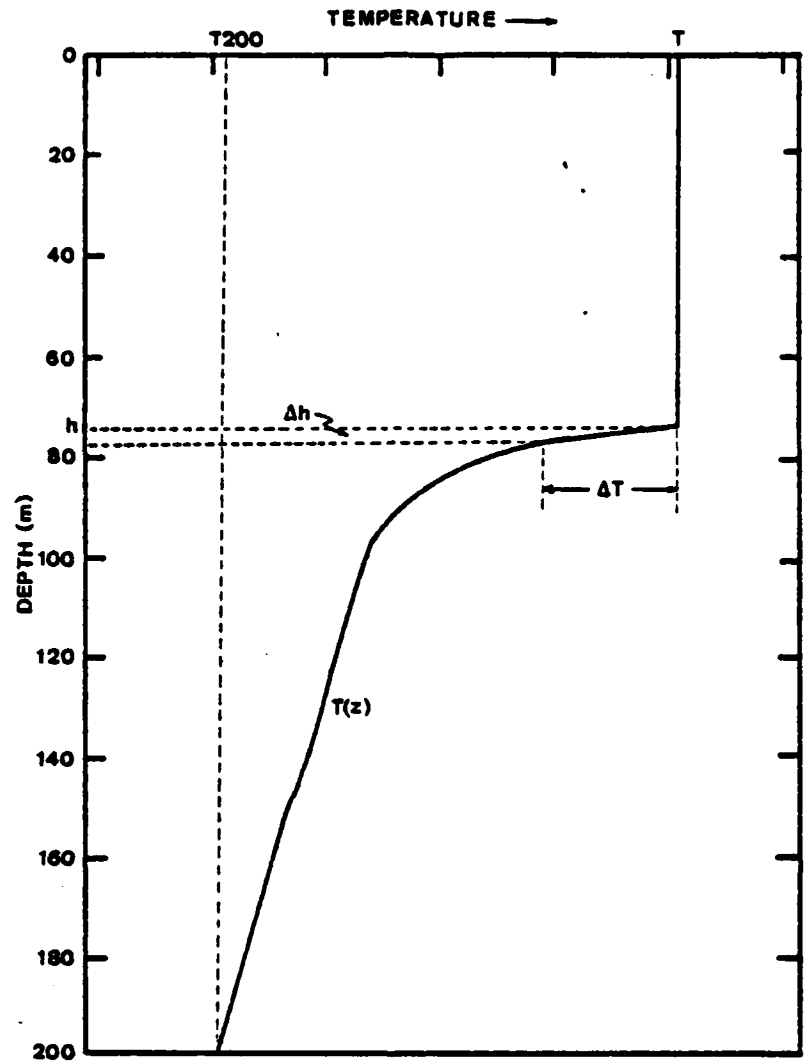

Figure 1. Idealized Temperature Profile for the Upper 200 M of the Ocean, (Warrenfeltz, 1980).

layer depth is called the MLD, and its average temperature is the MLT. In this study Δh, the depth jump increment, is 1 M, and Δt, the jump temperature used to initialize the studies, will be 0.2°C. The temperature below the MLD is a function of depth, normally decreasing to a specified constant temperature (T200) at z=200 M.

For typical conditions during the winter in mid to upper latitudes, the MLD is relatively large, while in the summer it is much shallower. On the other hand, the summer MLT is much higher than the winter MLT. These extremes are due to the large scale variation of the surface heat fluxes and the wind intensities in each season. Conditions of net incoming surface heat flux and weak winds are normally associated with a decrease in the MLD and surface warming. Strong winds and a net outgoing surface heat flux are associated with the deepening of the MLD and surface cooling. Thus, smaller time scale events, such as the diurnal cycle, hurricanes or even synoptic scale cyclones, can cause large fluctuations in the MLD and in the general structure of the upper 200 M of the ocean.

The MLD calculated from bathythermographic observations taken over a one year period at Ocean Weather Station PAPA (OWS P, 50°N, 145°W) is shown in Figure 2. These MLD calculations were defined as the depth where the temperature is 0.2°C less than the surface temperature. Also notice that these observations are irregularly spaced in time. The seasonal variability in the MLD is obvious. Additionally, there are short time scale changes caused by the diurnal cycle or synoptic scale events.

B. AN OPBL PREDICTION MODEL FOR DATA ASSIMILATION

There is presently no OPBL prediction model in operational use. However, as presented by Elsberry and Garwood (1980), the operational use of oceanic prediction models should become comparable in the next decade to the Numerical Weather prediction systems developed during the 1980's. It

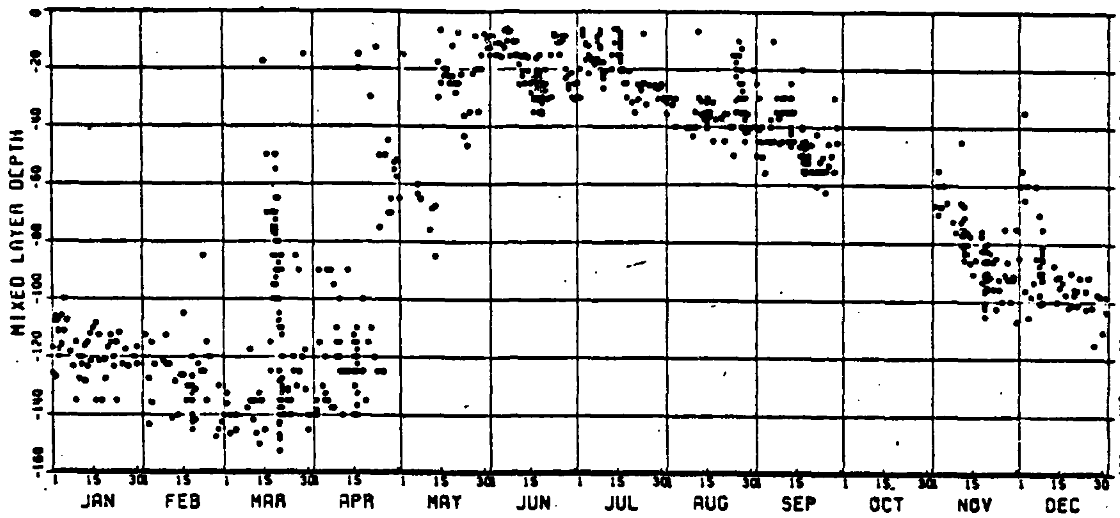

Figure 2. Mixed Layer Depths Determined From Bathythermographic Observations at OWS P During 1958, (Garwood and Adamec, 1980).

is imperative that a method for initialization of these models be developed. Data assimilation, as defined by McPherson (1975), requires that the numerical representation into which the observations are absorbed be governed by explicit physical constraints: i.e., a set of equations. The OPBL prediction model developed by Garwood (1977) will be used for the data assimilation technique.

This model is a 1-D, vertically integrated bulk model of the thermodynamic turbulent kinetic energy equations for the OPBL. An entrainment hypothesis which is dependent upon the relative distribution of turbulent energy between horizontal and vertical components is used as a mechanism for allowing both entrainment and retreat of the layer. There are two

properties that distinguish this model from earlier ones. The first property is that the fraction of wind-generated turbulent kinetic energy (TKE) used to increase the potential energy by means of deepening the mixed layer is dependent upon the layer stability. This results in the variation of the entrainment rate by the diurnal heating/cooling cycle. The second important property is the model's ability to maintain a cyclical steady state over an annual period by limiting the maximum layer depth (Garwood, 1977).

The model inputs are specified atmospheric conditions: wind speed, cloud cover, sea surface temperature, air temperature, and dew point. These observations were taken every three hours at OWS P and were interpolated to hourly values for use in the model. Although the Garwood model has provisions for salinity variations, no precipitation observations were available for the period of study. Thus, the salinity was held constant. Since the model is only 1-D, no considerations are made for horizontal advection. According to Denman and Miyake (1973), salinity variations and changes in the thermal structure at OWS P due to advection were both small and could be ignored for time scales of less than a month. Given the time-dependent fluxes of momentum and buoyancy, the model calculates the entrainment fluxes, mixed layer depth, mean layer temperature and salinity. Additional details of the model are provided by Gallacher and Garwood (1980).

Garwood and Adamec (1982) presented a series of one dimensional simulations using the atmospheric forcing data from OWS P. Figure 3 is an example of a year-long simulation during the year of 1959. Of particular interest in this example is the variability in the depth of the

isothermal layer. During the winter, the predicted isothermal depth was usually greater than 100 M, although appreciable fluctuations occurred on diurnal or atmospheric synoptic time scales. During the summer months, there was much less variation in the predicted isothermal depth, and the mean depth was much shallower than the mean depth during the winter. The layer labeled B has special relevance for this study. This is the depth at which the temperature is 0.2°C less than the surface temperature or the MLT. This depth will be referred to as the 0.2 method to finding the MLD. When used on the model outputs, as in Figure 3, this 0.2 method produced depths much larger and normally less variable than the model output predicted isothermal layer.

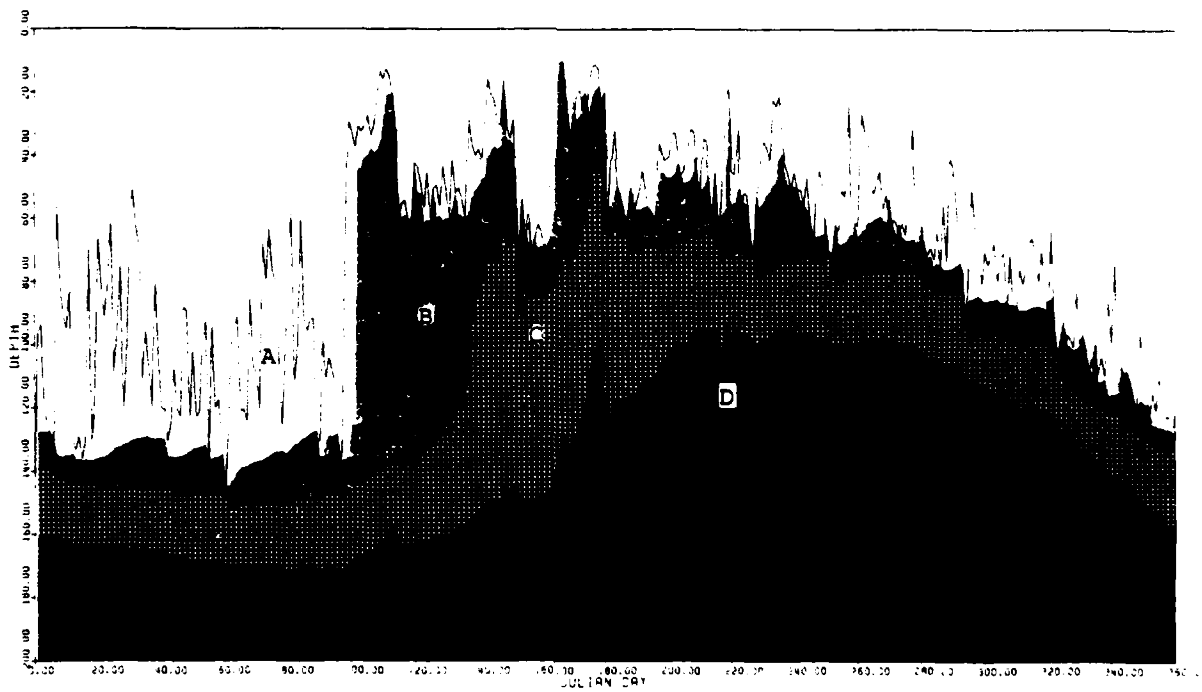

Figure 3. Model-predicted maximum daily depths of the well-mixed layer (solid), surface temperature minus 0.2°C (top of shaded) surface minus 1.0°C (top of cross-hatching), and surface temperature minus 2.5°C (bottom of cross-hatching) during 1959 at OWS P (Garwood and Adamec, 1982).

Figure 4 is an example of the model-predicted isothermal depths used in this study. A comparison of the depths defined using the 0.2 method from the same profiles that were used in Figure 4 is shown in Figure 5. There are large differences between the mean MLD in these two examples. The 0.2 method used for finding the MLD not only changed the absolute values of the MLD, but it is also insensitive to almost all of the small time scale fluctuations. This type of evolution is more consistent with the observations shown in Figures 4 and 5, except for a period having shallower depths around day 62. These differences in layer depth evolutions will be discussed later.

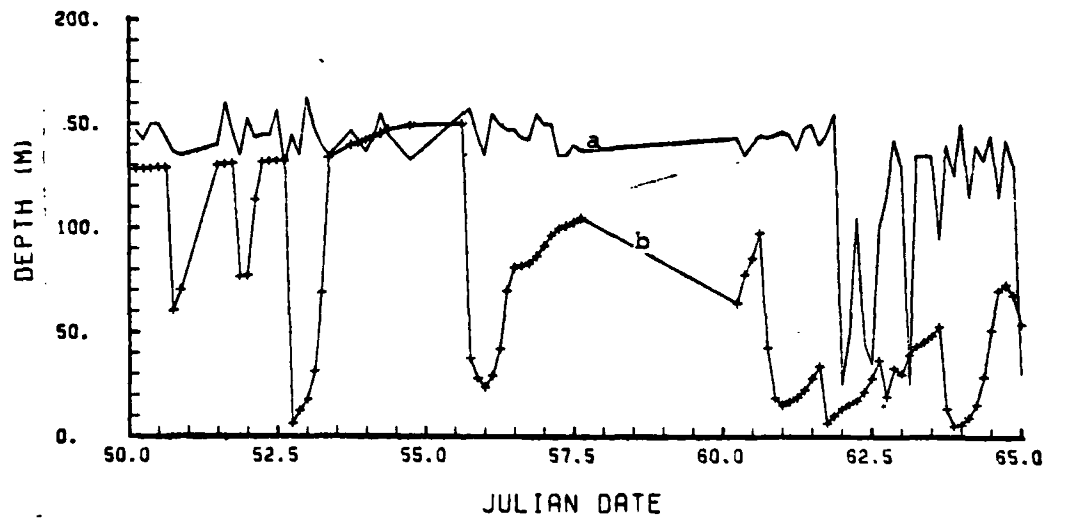

Figure 4. Model Output MLD's From This Study, observed MLD from actual data (solid line), model predicted MLD from climatology profile (+++).

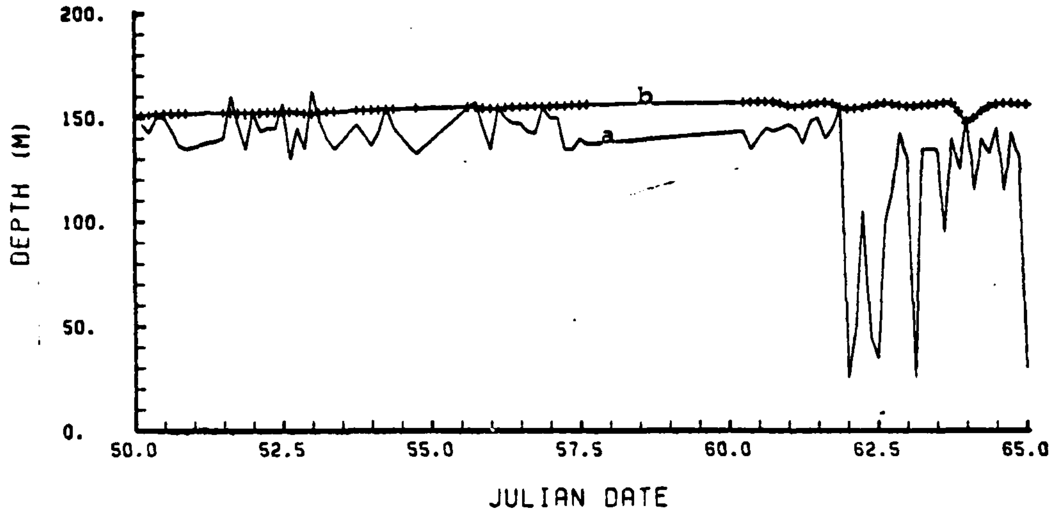

Figure 5. Calculated MLD from Model-Predicted Profiles in Figure 4 Using 0.2 Method, (solid line) same as Figure 4, (+++) predicted MLD using 0.2 method.

C. STUDY DESIGN

This study follows the research of Elsberry and Warrenfeltz (1981), hereafter referred to as EW. In the EW study, a data assimilation technique was developed that was stable when data were inserted during the model predictions. Various types of erroneous profiles were inserted in the model to test the sensitivity of the model to new profiles.

The hypothesis of both the EW study and this study is that using a data assimilation technique to incorporate available thermal structure information into an OPBL model run will improve forecasts of the oceanic MLD and MLT. In the EW study, the model predicted profiles during a 15-day period were used to select a random set of profiles to which random errors were added to simulate real temperature profiles. Julian

days 35-50 were chosen as a representative winter period. Using the model-generated profiles during the "history window", three types of 15-day predictions (days 50-64) were made, as indicated in Figure 6. One prediction was from the last available profile prior to day 50. The second prediction was made from the average profile made from advancing a number of the simulated profiles to day 50. The third prediction was made from the screen-averaged profile developed from only those simulated profiles with surface temperatures within 1.5 standard deviations of the mean surface temperature during the 15-day forecast window. Finally, control data were available for comparison from the model integration during the 15-day forecast window. If the original hypothesis was correct, then the errors made in the predictions from the averaged or screen-averaged data should have been less than the errors made in the predictions from the last available profile. The EW study also tested the effect of the number of simulated profiles that were required to produce accurate predictions: 5, 15, and 30 simulated profiles were used for assimilations and predictions. An illustration of how the group of five was created and used in the prediction window is shown in Figure 6. These groups will hereafter be referred to as the simulated averaged or screen-averaged groups of 5, 15, or 30.

The first phase of this experiment continued from the EW study using the MLD's and MLT's created in that study. This phase was designed to determine what the effect would be if the verification (control) profiles were: incomplete, but perfect; complete, but noisy; or incomplete and noisy. To simulate the first situation, subsets of the control data were created, but no errors were added. These subsets will be referred to as

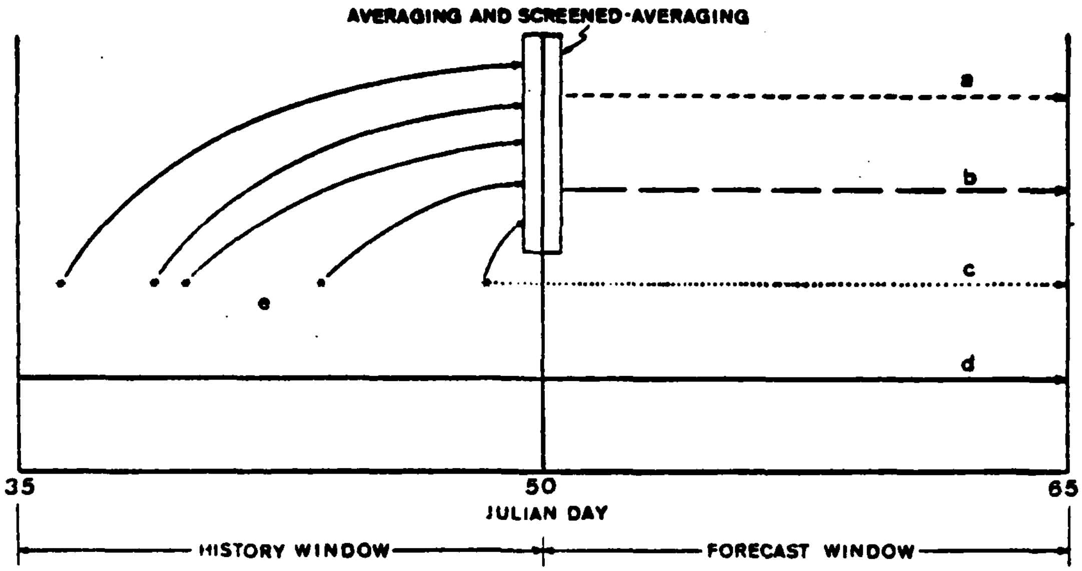

Figure 6. Data Assimilation Model (Elsberry and Warrenfeltz, 1981), (a) forecasts from average profile, (b) forecasts from screened-average profile, (c) forecasts from last available profile, (d) control data, (e) randomly selected history data group.

the perfect control groups of 5, 15, 30, and 50. The times of these verification profiles were selected by a random number generator. The errors of the predictions from the simulated averaged groups and from the last profile were compared with this incomplete but perfect verification information. The second situation, complete but noisy control data, was set up by adding normally distributed errors of known magnitude to the complete set of 120 control MLD's and MLT's. The last situation, incomplete and noisy, used the same randomly generated control groups of 5, 15, 30, and 50 with the normalized errors added. A model of the error

studies with the simulated last available and averaged profile predictions for each of the new verification sets is given in Figure 7. The verification tests will give an indication of how much verification data will be required to nearly reproduce the same results for the complete and perfect control data. Because the errors are known in the simulated verifications, one can test the effect of noisy data. The purpose of these tests is to provide a background for interpretation of the actual ocean data studies described below.

Phase two of this study is to insert actual BT data from OWS P into the model and do the same error studies as in the simulated situations above. Predictions will be made from the assimilated BT's, from the last profile before the forecast window and from a climatological profile developed from the average conditions in the forecast window for all the years being studied. The latter case might represent a situation in which no data are available in the history window. In this case, climatological data are used to initialize the model. Forecasts will be compared to the actually observed profiles during the forecast interval. These error studies will also be compared to persistence, which is a "forecast" that conditions do not change from the last profile from the data window. A final "forecast" is to specify the total averaged MLD's and MLT's from the years studied. If the original hypothesis holds, the MLD and MLT predictions from the assimilated profiles should yield the smallest errors compared to persistence, predictions from an initial climatological profile, the last profile in the history window or the overall averaged MLD's and MLT's.

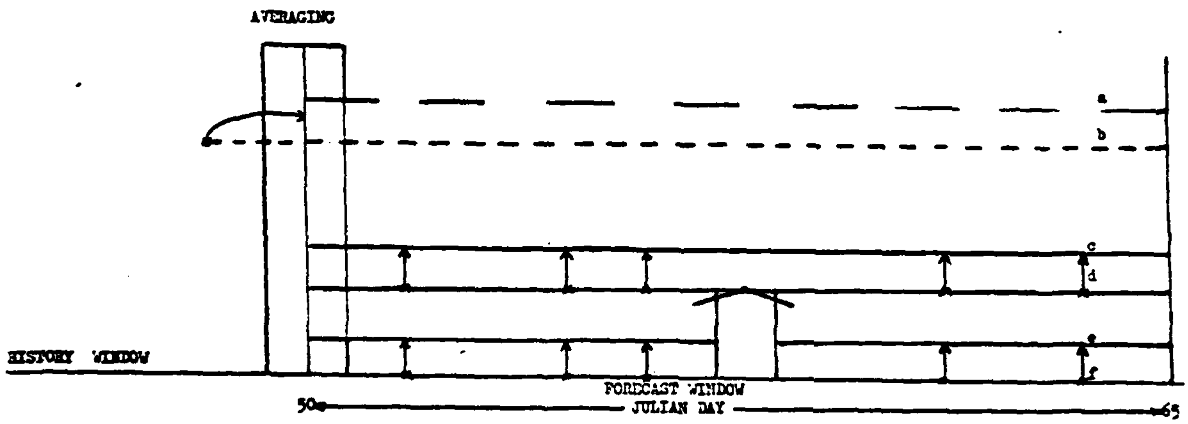

Figure 7. Control Data Group Preparation Model: (a) EW average of 15 predicted data set, (b) EW last of 15 predicted data set, (c) noisy and incomplete control group, (d) complete and noisy control group (e) perfect but incomplete control group, (f) EW control data set.

II. PHASE ONE

A. ELSBERRY AND WARRENFELTZ RESEARCH

The objective of this phase was to show that data assimilation techniques similar to the atmospheric approaches reviewed by McPherson (1975) could be used to initialize a model such as that developed by Garwood (1977). In the EW study, temperature profiles were generated from annual simulations using the Garwood model. These model-generated profiles were stored each three hours during both winter and summer 30-day periods. Actual atmospheric forcing conditions collected at Ocean Weather Station PAPA for 14 different years were used to drive the Garwood Ocean Model. Since Garwood's model was used to generate the data, if any one time period from the data window was used to reinitialize the model, the new profiles generated into the forecast window would have been the same as those already generated. Thus, random errors were added and normally distributed to the profiles in the data window, while those in the forecast window were not changed. The errors were due only to the assimilation technique, since the verification data were error free.

This assimilation technique was tested with various sets of profiles randomly selected within the data window. The profiles from the forecast window were stored at the same three hour periods as those in the control data. For each group and at each three hour time period, the Root Mean Square (RMS) errors were found between the forecast from the control data versus the assimilated groups and the last of each group. The mixed layer temperature and the isothermal or mixed layer depth RMS errors were

collected for each three hour period and for all fourteen years. It was found that the predictions from the last profile of each group had errors three to five times the errors of the predictions from the assimilated data when averaged over the entire fourteen years. It was also found that this assimilation, even on groups as small as five profiles during the history window, gave results comparable to predictions from initial data profiles generated from much larger groups. Table 1 shows the final results found in the EW study for the averaged and the last of 15.

TABLE 1

Root-mean square errors for the predictions from the average of 15 and last of 15 profiles compared to the control group, after Elsberry and Warrenfeltz (1981).

SEASON	GROUP SIZE	GROUP TYPE	RMS h ERROR (M)	BIAS h	RMS T ERROR (C)	BIAS T
WINTER	15	LAST	45.80	3.30	0.21	0.02
		AVG	13.10	5.60	0.09	-0.06
SUMMER	15	LAST	6.74	-0.07	0.76	0.12
		AVG	0.80	0.18	0.24	-0.10

B. SIMULATED VERIFICATION DATA

The model-predicted MLD's and MLT's from the simulated last profile in the group of 15 and the simulated averaged group of 15, along with the complete and perfect (control) data, were used in this phase of this study. Thus, each forecast window had 120 predicted MLD and MLT values from each simulated group for comparison with an equal number of control MLD and MLT values.

Random errors were added to the control data to make the control data appear as realistic as possible. Estimated "observational" errors in MLD and MLT during summer and winter were chosen (Table 2). Because the summer temperatures fluctuate appreciably compared to the winter temperatures, an estimated error of 1.25°C was used in the summer. These errors were inserted into the control data by adding normalized standard deviations about the average MLD and MLT errors at randomly selected time periods. Thus, some percentage of the specified MLD and MLT error was added to the existing MLD and MLT. These errors were normally distributed between -3 to 3 standard deviations, taking the specified errors in each category to be one standard deviation. A total of 50 noisy verification MLD and MLT values was again divided into four new subgroups. The characteristics of these new noisy control groups is indicated in Table 3.

TABLE 2

Magnitude of the randomly added errors added to the verification mixed layer depth (h) and temperature (T) during each season.

Season	h	T
WINTER	10 M	0.25°C
SUMMER	3 M	1.25°C

TABLE 3

Statistics from the subsets of verification data.

SEASON	GROUP SIZES	AVG MLD (M)	STD MLD	AVG MLT (C)	STD MLT
WINTER	5	83.09	39.40	5.23	0.51
	15	81.85	41.74	5.24	0.53
	30	82.32	41.21	5.23	0.53
	50	82.25	40.23	5.23	0.51
SUMMER	5	11.44	6.86	12.26	1.29
	15	9.28	6.64	12.38	1.32
	30	10.80	6.92	12.50	1.31
	50	10.41	6.72	12.44	1.28

Some of the years used in the EW study had to be omitted because the observations to be used in the latter half of this study were not available. Table 4 is a list of the years used for the winter and summer tests with real data. Repetition of the error studies done by EW for the smaller set of years in Table 4 produced no appreciable differences. The results in Table 5 are similar to those in Table 1.

A major simplification in the selection of the subsets is that the time periods randomly selected in the first year are used in all of the years studied. This ensures consistency in the sample sizes at each time interval and allows a display of the time dependence of the error magnitude. However, all tests were also conducted by letting the noisy control time periods change each year. Sample sizes were inadequate to display the time dependence of the errors. For example, a sample of five

TABLE 4

Summer and winter years (first two digits omitted) used in the real data tests.

	WINTER
YEARS	56,57,58,60,61,62,63,64,65,67,69
	SUMMER
YEARS	53,55,56,57,58,60,61,62,63,64,65,67,68

TABLE 5

Similar to Table 1 for the years indicated in Table 4 rather than the 14 year sample used in the EW study.

SEASON	GROUP SIZE	GROUP TYPE	RMS h ERROR (M)	BIAS h	RMS T ERROR (C)	BIAS T
WINTER	15	LAST	45.36	2.94	0.23	-0.00
		AVG	13.16	5.95	0.09	-0.07
SUMMER	15	LAST	6.55	-0.24	0.75	0.19
		AVG	0.76	0.12	0.23	-0.08

profiles per year for 11 years gives 55 entries in the 120 possible 3-hourly verifications. At best, one can summarize the overall errors during the 15-day forecast window. The numerical results from the overall samples are very similar. The overall RMS errors are indicated in Table 6 for the case with the same verification times each year and in Table 7 for the case with different times each year.

TABLE 6

RMS Errors of the predictions from the last and the average of 15 profiles when different subsets of the noisy verification data are used. The expected errors are the comparisons when the complete set of 120 verification intervals is used.

SEASON	GROUP SIZE	GROUP TYPE	RMS h ERROR (M)	BIAS h	RMS T ERROR (C)	BIAS T
WINTER	5	LAST	47.16	5.15	0.34	0.00
		AVG	19.30	6.04	0.29	-0.06
	15	LAST	51.61	-2.52	0.36	-0.00
		AVG	16.06	6.39	0.26	-0.07
	30	LAST	46.40	0.47	0.34	0.01
		AVG	14.51	4.91	0.26	-0.05
	50	LAST	47.40	0.15	0.34	0.01
		AVG	16.03	5.58	0.26	-0.06
EXPECTED ERRORS:		LAST	46.86		0.33	
		AVG	16.46		0.27	
SUMMER	5	LAST	7.73	-0.53	1.72	0.29
		AVG	3.38	-0.52	1.40	0.01
	15	LAST	6.72	-1.96	1.52	0.26
		AVG	2.96	-1.14	1.29	-0.10
	30	LAST	6.68	-1.01	1.51	0.22
		AVG	3.10	-0.78	1.28	-0.03
	50	LAST	7.00	-1.29	1.54	0.24
		AVG	3.08	-0.91	1.30	-0.05
EXPECTED ERRORS:		LAST	7.38		1.46	
		AVG	3.10		1.27	

TABLE 7

Similar to Table 6, except using random time periods for the verification intervals for each year.

SEASON	GROUP SIZE	GROUP TYPE	RMS h ERROR (M)	BIAS h	RMS T ERROR (C)	BIAS T
WINTER	5	LAST	51.37	0.17	0.32	-0.00
		AVG	18.41	8.18	0.25	-0.10
	15	LAST	46.58	2.88	0.36	0.01
		AVG	16.22	5.27	0.26	-0.06
	30	LAST	44.32	-1.78	0.34	0.02
		AVG	15.70	4.74	0.27	-0.05
	50	LAST	46.21	-0.22	0.35	0.01
		AVG	15.93	5.21	0.26	-0.06
SUMMER	5	LAST	5.63	-0.59	1.54	0.22
		AVG	2.94	-0.87	1.36	0.03
	15	LAST	6.84	-0.98	1.52	0.12
		AVG	2.81	-0.56	1.24	-0.13
	30	LAST	6.45	-0.80	1.54	0.25
		AVG	3.05	-0.72	1.29	-0.02
	50	LAST	6.48	-0.80	1.53	0.22
		AVG	3.05	-0.66	1.28	-0.05

The numbers are not identical, but the conclusions regarding the superiority of the use of assimilated profiles versus using the last available profile is not changed. Thus, time dependence of the errors (which are presumed to be random as in these simulations) is irrelevant, the errors may be accumulated from many different samples to distinguish major

differences in forecast errors. Figures 8 and 9 represent the RMS error studies from the EW tests and from the noisy and incomplete verification data sets of 5 and 50. The solid lines are similar to those obtained in the EW study, and indicate the time dependency of the errors. The symbols are from the comparisons of the noisy verification subsets versus the predictions from the last and average of 15 in the EW study. Notice that the magnitudes of the errors from the complete verification data in the EW study and the incomplete but noisy situation are very close in magnitude in Figure 8. However, this is not the case in Figure 9. The reason for this difference in the incomplete but noisy case is that the expected total errors would be the square root of the sums of the squares of the RMS errors in each group being compared. Since the simulated errors are known for each group of predictions and the average error by

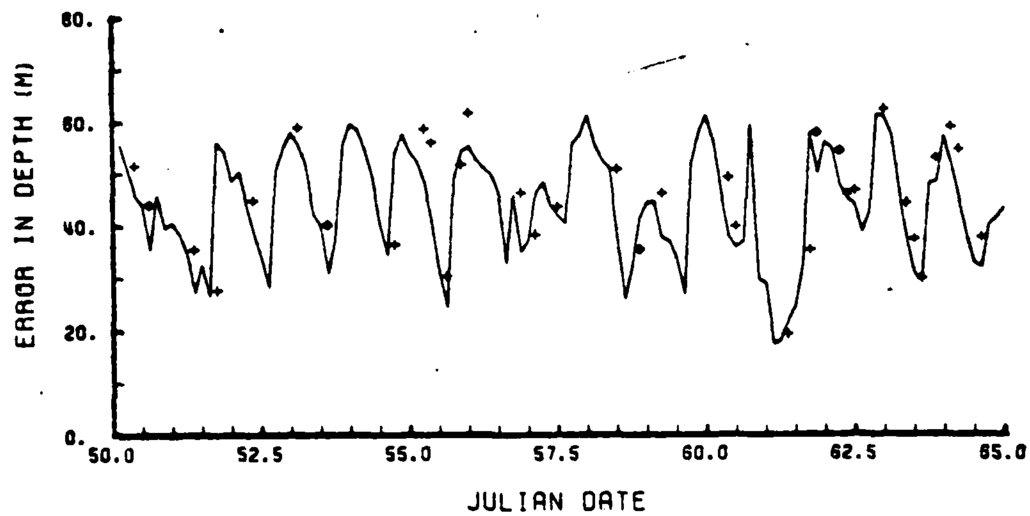

Figure 8. Winter Regime 11 Year RMS MLD Errors, simulated last of 15 vs. control (line), simulated last of 15 vs. noisy control group of 30 (+++), simulated last of 15 vs. noisy control group of 5 (◆◆◆).

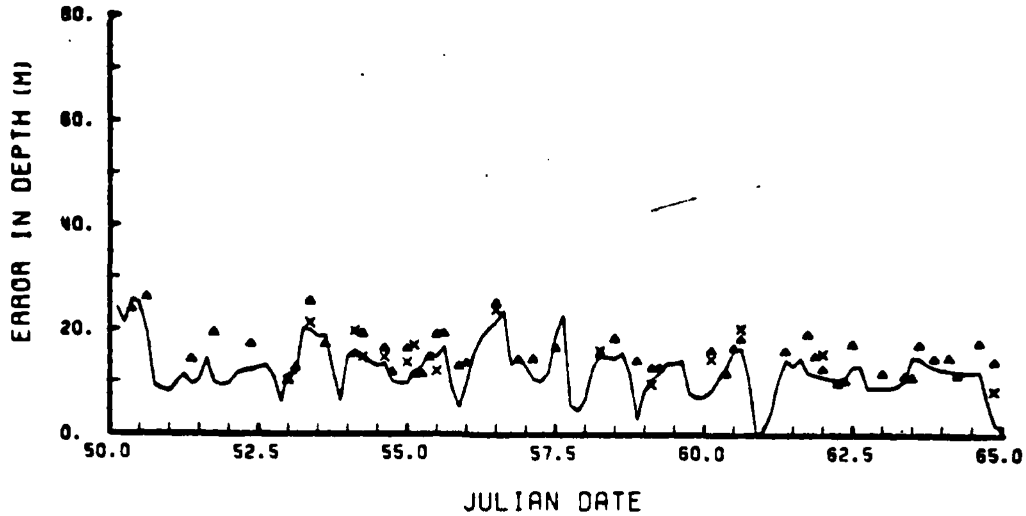

Figure 9. Winter Regime 11 Year RMS MLD Errors, simulated average group of 15 vs. control (line), simulated average of 15 vs. noisy control group of 50 (ΔΔΔ), simulated average of 15 vs. noisy control group of 15 (XXX).

definition is known for each noisy group, then the total error should be easy to estimate. Given enough verification data in the previous two figures, these results were as expected. If relatively large observational errors are added to large errors arising from the prediction, the result is a large error, as in Figure 8. On the other hand, if a large observational error is added to a small prediction error, the resultant error will be larger than the small prediction error, as in Figure 9. The time dependency that is indicated from the complete verification data set is no longer displayed from the subsets of data. Even though the resultant errors are predictable for noisy subgroups of the verification data, the time dependence will be lost if the control group is

not complete. Even without this time dependency the better prediction technique may be determinable.

An attempt was made to represent the time dependent error that is comparable to that shown in Figure 8. Each point in Figure 10 represents an average error for a set of random times. For example, the first + in Figure 10 is an average of the first RMS MLD error from each of the 11 years. By contrast, the first RMS MLD error displayed in Figure 8 is from the same time period in each of the 11 years. Each point in Figure 10 is plotted at the average of the 11 verification times that comprise that point. This use of different verification times each year requires this smoothing technique. There is very little difference between these two graphs, although some of the detailed characteristics have changed. The remainder of this phase of the study will use the tests with the verification data at the same time periods each year.

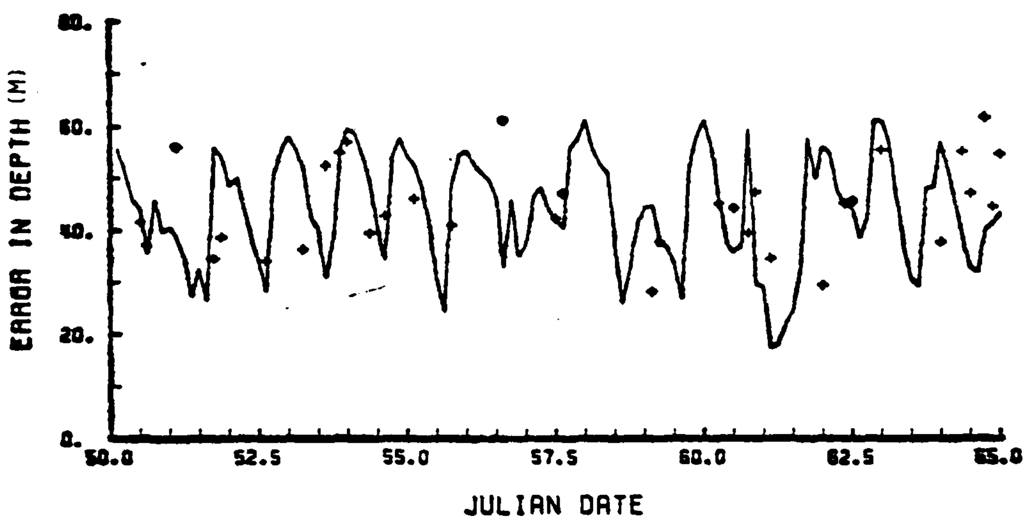

Figure 10. Winter Regime Random 11 Year RMS MLD Errors, simulated last of 15 vs. control (line), simulated last of 15 vs. noisy control group of 30 (+++), simulated last of 15 vs. noisy control group of 5 (◆◆◆).

C. RMS ERROR CALCULATIONS

1. Control Group Statistics

The overall error statistics using the incomplete but perfect (situation 1) verification subsets are summarized in Table 8. The primary conclusion is that all of the groups approach the expected values within the appropriate season. That is, given at least 11 years of data, the statistics for large and small groups tend to approach the complete verification data averages and standard deviations. Thus, even with small groups of verification data, we are able to use the overall RMS errors to distinguish between these two methods of initializing the Garwood model. These overall statistics do not indicate the time dependence of the errors.

2. Winter Regime

During the winter, the RMS MLD errors from the EW study for the simulated average group of 15 and the simulated last of 15 were well seperated. Although the RMS errors in MLT were small for both types of initial profiles, these errors were easy to differentiate when compared to the complete control data.

With incomplete but noisy (situation 2) verification data, it was expected that the RMS error would be a vector sum of the predicted errors in the EW experiment and the observational error introduced. Figure 11 is a comparison of the RMS MLD errors from the simulated last of 15 in the EW study to the RMS MLD errors in the noisy verification groups of 30 and 5. When these two groups are compared, the RMS error for the complete verification set should be

$$[(10.0M)^2 + (45.36M)^2]^{\frac{1}{2}} = 46.45M,$$

TABLE 8

Similar to Table 6, except with incomplete but perfect (noise) free) control subsets.

SEASON	SUBCONTRL GROUP SIZE	SIMUL GROUP TYPE	RMS h ERROR (M)	BIAS h	RMS T ERROR (C)	BIAS T
WINTER	5	LAST	45.36	5.56	0.24	-0.00
		AVG	16.53	6.45	0.09	-0.07
	15	LAST	50.98	-2.16	0.24	-0.00
		AVG	13.30	6.74	0.09	-0.07
	30	LAST	44.47	1.33	0.23	-0.00
		AVG	12.48	5.78	0.09	-0.07
	50	LAST	46.74	0.70	0.23	-0.00
		AVG	13.19	6.13	0.09	-0.07
EXPECTED ERRORS:		LAST	45.36		0.23	
		AVG	13.16		0.09	
SUMMER	5	LAST	6.67	-0.17	0.76	0.19
		AVG	1.60	-0.16	0.24	-0.09
	15	LAST	6.65	-1.65	0.77	0.27
		AVG	1.66	-0.82	0.23	-0.08
	30	LAST	6.17	-0.69	0.71	0.16
		AVG	1.54	-0.47	0.23	-0.08
	50	LAST	6.37	-0.93	0.73	0.20
		AVG	1.59	-0.54	0.23	-0.08
EXPECTED ERRORS:		LAST	6.55		0.75	
		AVG	0.76		0.23	

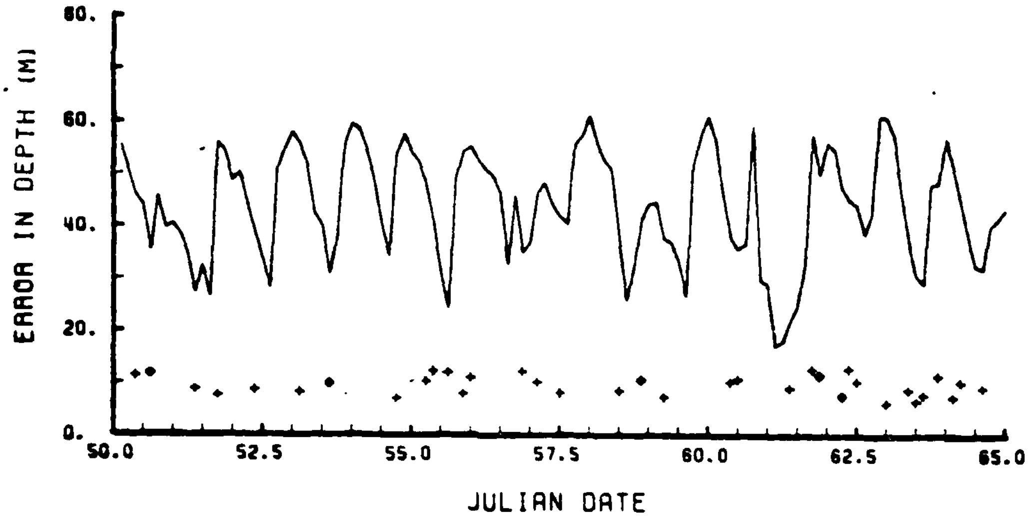

Figure 11. Winter Regime RMS MLD Errors, simulated last of 15 vs. control (line), noisy control group of 30 vs. control (+++), noisy control group of 5 vs. control (◆◆◆).

using values from Tables 2 and 5. The actual winter MLD errors using the last profile (Table 6) are 46.40 M for the noisy group of 30 and 47.16 M for the noisy group of 5. The expected resultant RMS error was approached even for small groups of verification data. Similar results were found for the other comparisons in Table 6. For various reasons, real data will have unknown errors in both the assimilation and verification data. A determination needs to be made whether the RMS errors from the simulated averaged predictions are significantly less than those from the simulated last predictions. From these comparisons it is clear

that in this case the assimilation technique provided better MLD predictions than did the last of 15 group. If the verification data are too noisy, then the RMS errors from each simulated group above will be indistinguishable. Figures 12 and 13 show the comparisons of RMS MLT errors from each simulated group above to the RMS MLT errors of the noisy verification groups of 50 and 15. The RMS errors of the noisy groups are much larger than the RMS errors from the simulated average group of 15 (Figure 13). On the other hand, the same RMS noisy control errors are about the same as the RMS errors of the simulated last group of 15 (Figure 12). Therefore, from a comparison of the simulated average group versus the noisy control groups, it is expected that their resultant RMS error will be higher than the average group's original RMS error. While

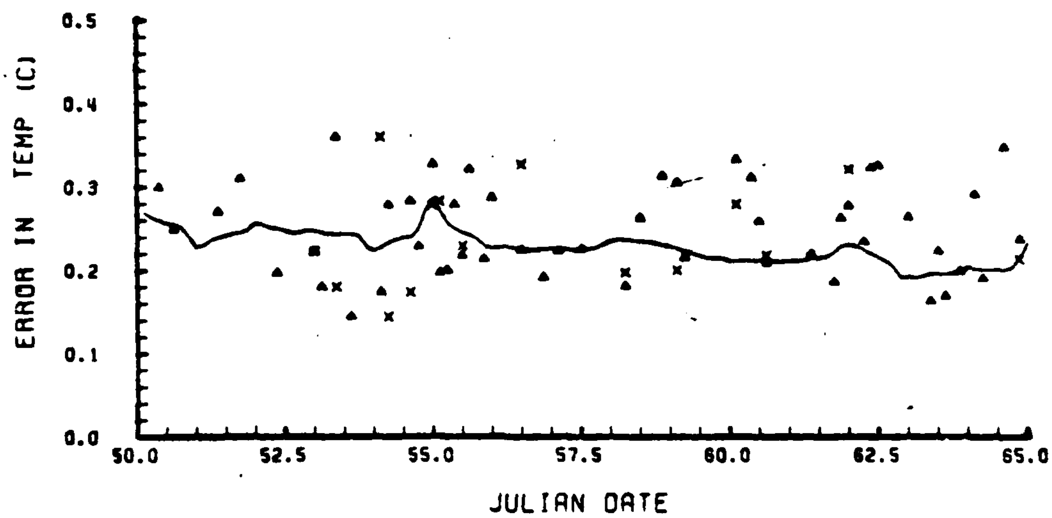

Figure 12. Winter Regime RMS MLT Errors, simulated last of 15 vs. control (line), noisy control group of 50 vs. control (ΔΔΔ), noisy control group of 15 vs. control (XXX).

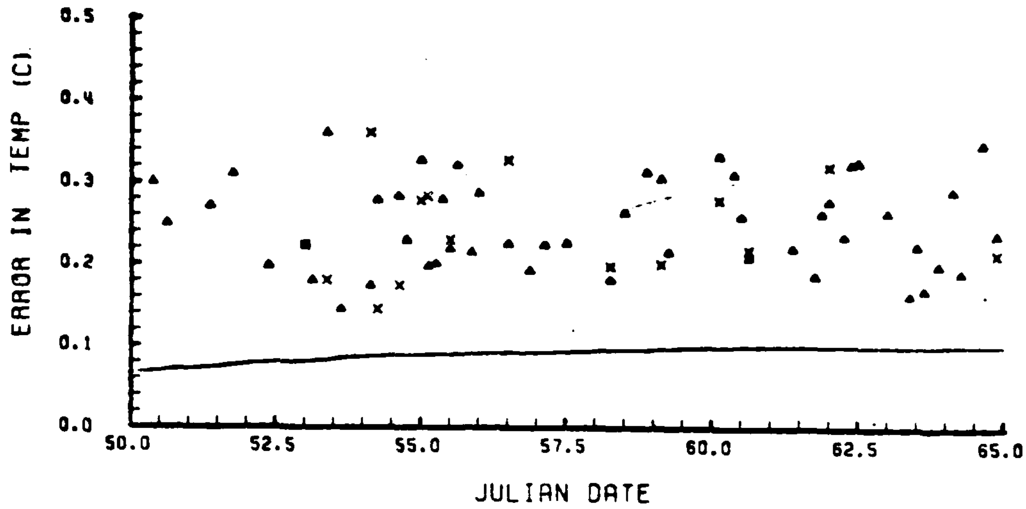

Figure 13. Winter Regime RMS MLT Errors, simulated average of 15 vs. control (line), noisy control group of 50 vs. control (ΔΔΔ), noisy control group of 15 vs. control (XXX).

comparing these same noisy control groups to the simulated last of 15, it is expected that the resultant error will not be very much larger than the initially large errors. The final conclusion is that it will be very difficult to differentiate which prediction system will be the best. Figure 14 and Figure 15 show that this is indeed the case. However, the overall statistics in Table 6 show that the assimilation technique did slightly better than the last of 15 group. The noise in the verification MLT's would be too large and the resultant RMS errors would be too close to determine a superior technique with only a small verification sample available.

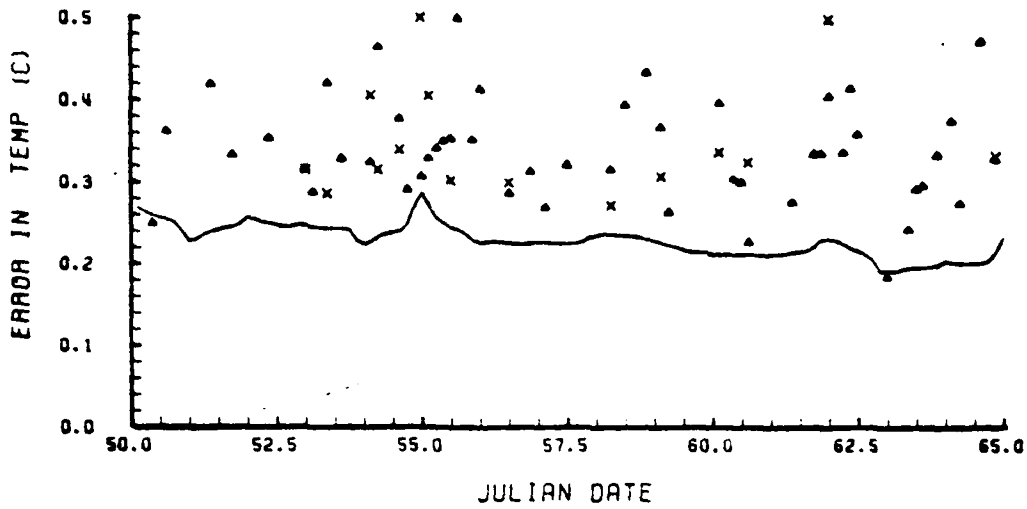

Figure 14. Winter Regime RMS MLT Errors, simulated last of 15 vs. control (line), noisy control group of 50 vs. simulated last of 15 (ΔΔΔ), noisy control group of 15 vs. simulated last of 15 (XXX).

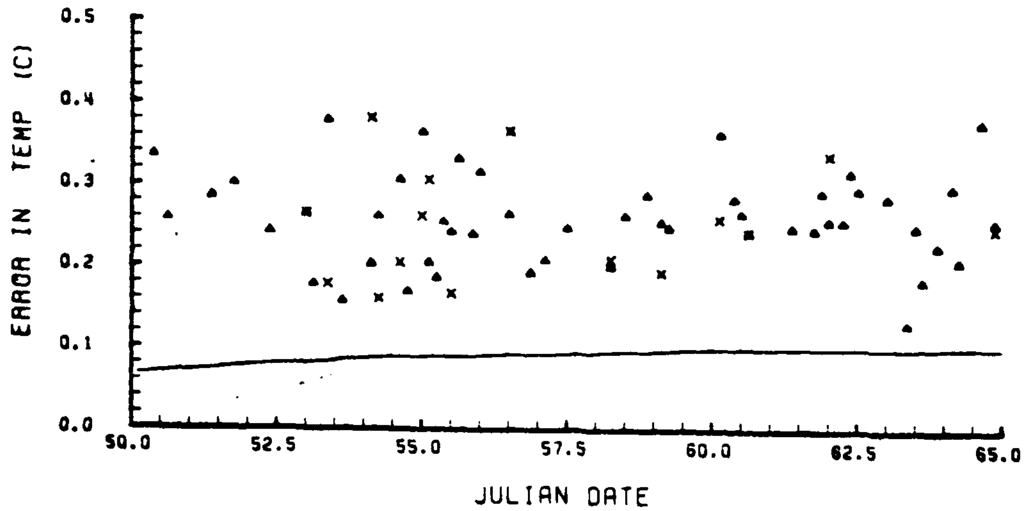

Figure 15. Winter Regime RMS MLT Errors, simulated average of 15 vs. control (line), noisy control group of 50 vs. simulated average of 15 (ΔΔΔ), noisy control group of 15 vs. simulated average of 15 (XXX).

3. Summer Regime

As was already pointed out in the winter regime, the incomplete but perfect case (situation 1) did achieve the expected results. That is, there were no significant differences in the overall statistics as indicated in Table 8. The incomplete and noisy case (situation 2) is also very similar to the winter regime. Figures 16 and 17 clearly demonstrate that the RMS MLD errors from the assimilated predictions were still smaller than the predictions from the last of 15. As in the winter regime, Figure 18 and Figure 19 show that the RMS MLT errors from the simulated average of 15 are very close to the errors from the simulated last of 15. From the tables, one can see that given enough data, the

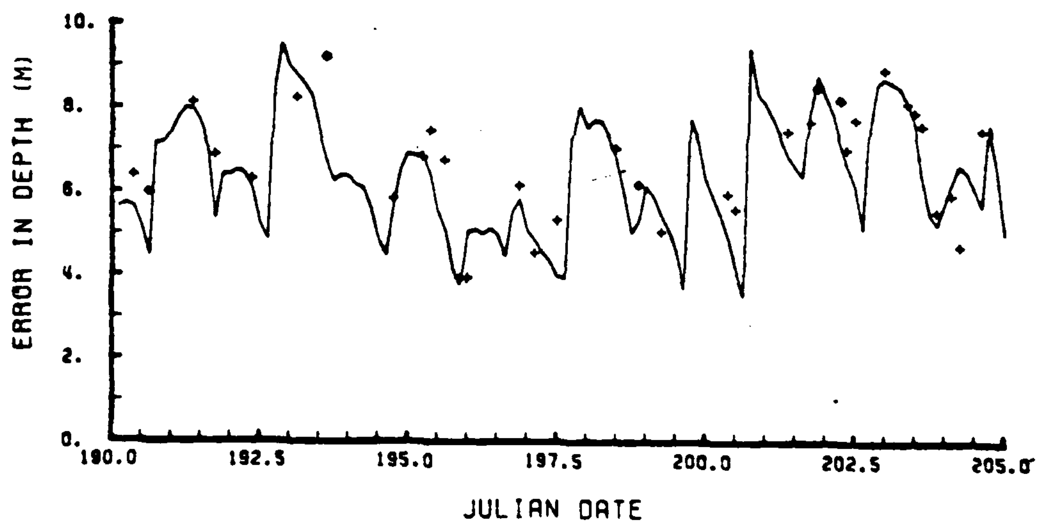

Figure 16. Summer Regime RMS MLD Errors, simulated last of 15 vs. control (line), noisy control group of 30 vs. simulated last of 15 (+++), noisy control group of 5 vs. simulated last of 15 (◆◆◆).

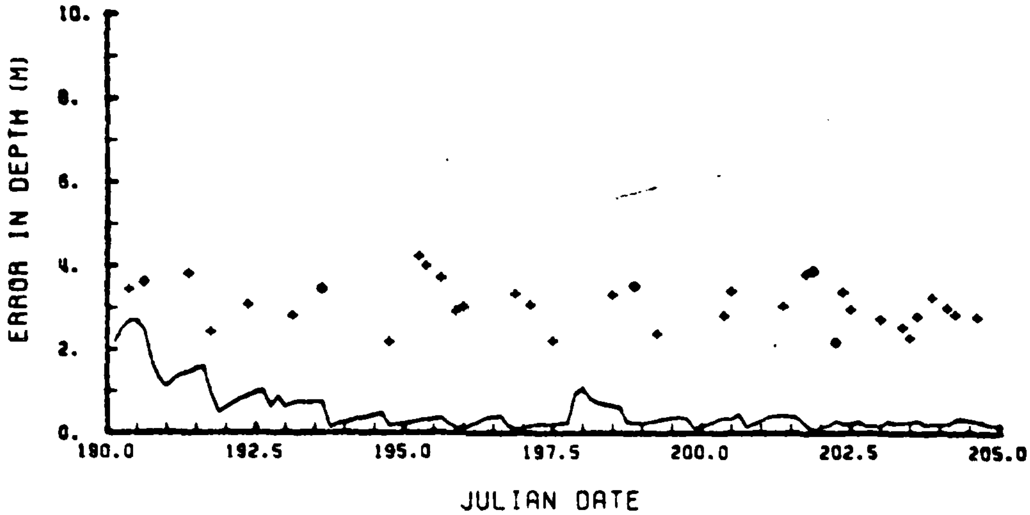

Figure 17. Summer Regime RMS MLD Errors, simulated average of 15 vs. control (line), noisy control group of 30 vs. simulated average of 15 (+++), noisy control group of 5 vs. simulated average of 15 (◆◆◆).

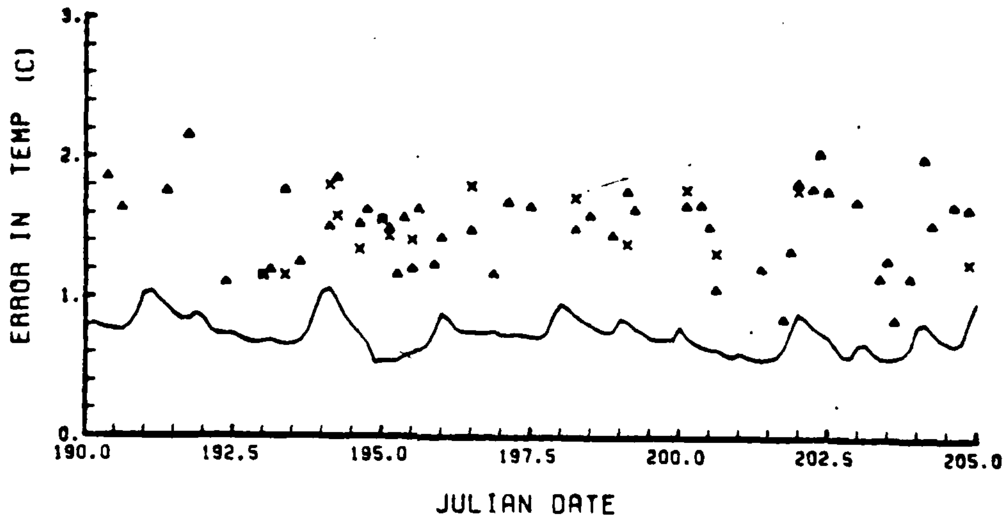

Figure 18. Summer Regime RMS MLT Errors, simulated last of 15 vs. control (line), noisy control group of 50 vs. simulated last of 15 (ΔΔΔ), noisy control group of 15 vs. simulated last of 15 (XXX).

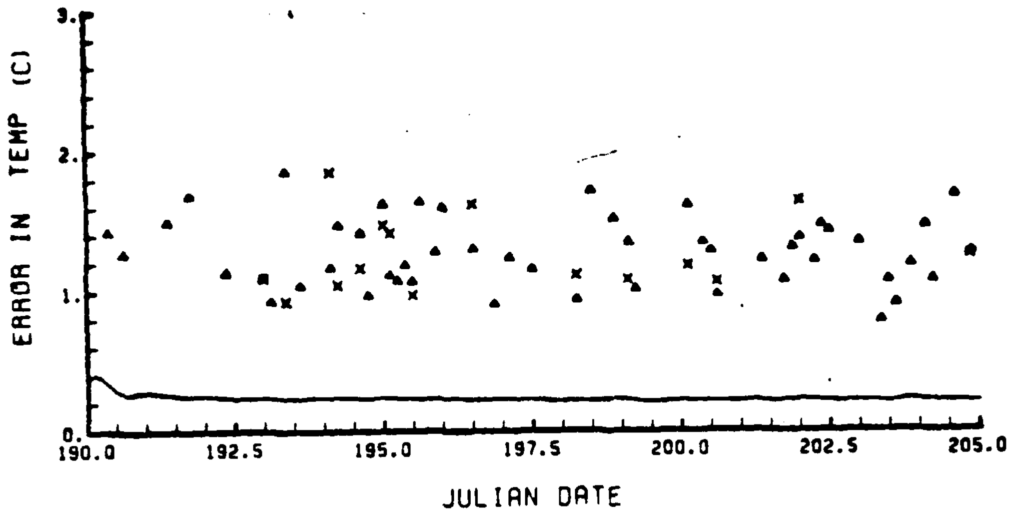

Figure 19. Summer Regime RMS MLT Errors, simulated average of 15 vs. control (line), noisy control group of 50 vs. simulated average of 15 (ΔΔΔ), noisy control group of 15 vs. simulated average of 15 (XXX).

assimilation technique is still best. But as before, the differences are not apparent from the graphs in Figures 18 and 19, so one would not really be able to tell which predictions would be the best in limited data conditions.

4. <u>Results From Phase One</u>

Using at least 11 years of data with assimilation and verification groups of various sizes, it should be possible to determine the best prediction technique. This is the "expected" errors in Tables 6 and 8. As stated earlier, if the smaller groups of noisy control data compared to the predicted groups produced RMS errors nearly equal to the expected RMS errors, then detailed studies with complete and perfect data

are not necessary. It was noted that if the noise levels were too high, then the prediction errors could be concealed. In both seasons, the comparisons of the noisy control MLT values to each of the prediction group MLT values proved to be too noisy to deduce the superior method. Given enough data, the overall results over the entire 15 day period allowed a determination of which prediction set was better.

III. PHASE TWO

A. DATA PREPARATION

Based on the EW study, it was anticipated that groups of 15 or less bathythermographs in the history window and the forecast window would yield distinct comparisons. The actual BT profiles were extracted for each window during both the summer and winter regimes. There was generally an abundance of data available during the years studied in EW. However, three years during the winter regime (1953, 1955, and 1968) did not contain any BT profiles in the 15 day verification window. In the summer regime, only one year (1969) had insufficient BT profiles. For this reason, the earlier studies in Phase One were repeated using only the years that real data were available for each regime. As mentioned above, there was no degradation in the overall results if either 11 or 13 years were used rather than the 14 year sample.

The available OWS P temperature profiles were digitized every 5 M. The vertical interval in the model was 1 M to a depth of 200 M. One of the required inputs into the Garwood model is an initial estimate of the MLD. The MLD criteria for this study was chosen as the first level at which the temperature was 0.2°C less than the surface temperature, i.e., the 0.2 method. Some of the profiles did not extend to 200 meters. If these profiles did have a determinable MLD, the profile was completed by linear interpolation from the last reported temperature to the climatological temperature at 200 meters. During the winter, a value of 4.01°C

was used; during the summer regime, 4.28°C was used. Figure 20 is an example of an incomplete profile that was interpolated to the 200 M level. Both the original BT profiles and the interpolated values are indicated. A complete profile only reguiring interpolation between 5 M depth intervals is shown in Figure 21. Included on both of the figures is the climatological profile that was developed from the entire sample of profiles. This profile was developed from the average surface temperature, the average MLD and the average temperature at 200 M. The jump was set at 0.2°C and the thermocline was developed by a linear interpolation from the MLD to 200 M.

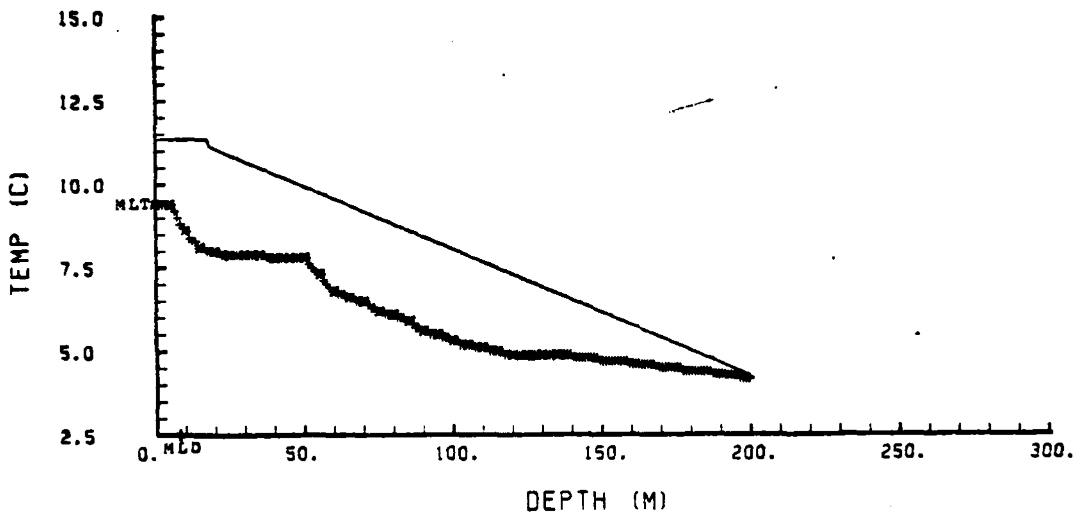

Figure 20. Summer Regime Modified Temperature Profile, climatology profile (line), original BT profile, every 5 meters (XXX), interpolated profile, every 1 meter (+++), MLD and MLT labeled.

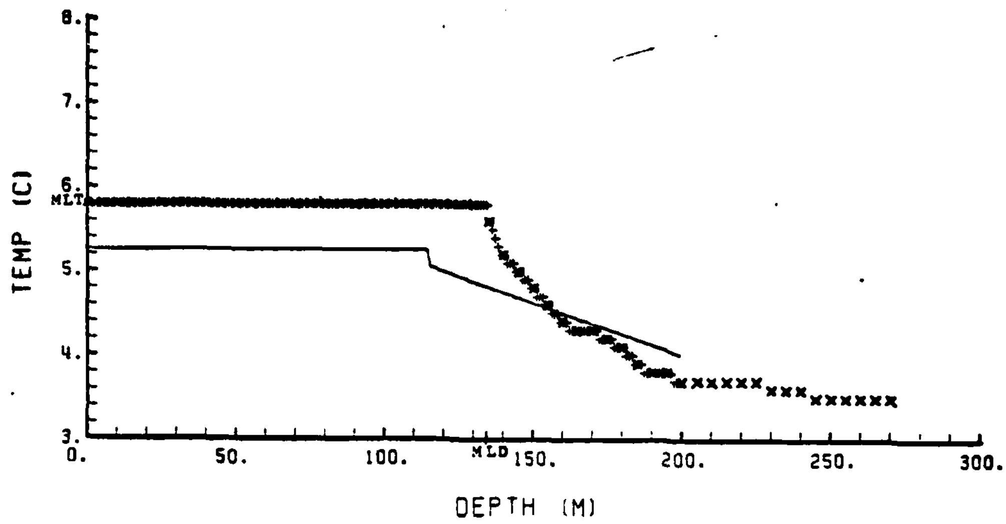

Figure 21. Winter Regime Modified Temperature Profiles, (line) same as Figure 20, (XXX) same as Figure 20, except using a complete profile, (+++) same as Figure 20.

Several years were found to contain over 100 profiles during both the history and forecast windows. That is, this particular location had an abundance of data rather than having inadequate and irregular observations. To provide a more realistic test, those years with large amounts of data in the history window were re-examined. A maximum of 30 profiles was permitted. Alternate profiles, or groups of profiles, were removed to reduce the sample size to less than 30 in the history window. This technique tended to ensure that the profiles would be well spread over the entire history window. The observational sample size in the

forecast windows was not reduced since the larger verification sets improve the significance of the results. For consistency with the simulated profiles in EW, it was desirable that the profiles in both the history and forecast windows were at three-hour intervals. The profiles were therefore moved forward or backward in time to the nearest three-hour period. However, there was now more than one profile at many of the three-hour intervals. For these periods, the profiles were simply averaged at all 1 meter levels. The new averaged profiles were then re-screened using the 0.2 method to determine the new MLD and MLT for that averaged profile.

B. MODEL RUNS

The observed profiles were inserted in the model in exactly the same manner as was done in the simulated runs. The EW study indicated that a time-weighted average for the assimilation was not required. That is, each advanced profile was given equal weight in the averaging regardless of the time interval over which the observation had been advanced by the model. However, it was possible that a time-weighted average during assimilation might produce better predictions. Seperate tests were made with and without time-weighting.

In the EW study, the assimilated profile predictions were compared only to the predictions from the last of that group. In this study, the assimilated predictions will also be compared to a model prediction that begins from the climatological profile, a prediction of no change from the last profile in each history window (persistence) and a "forecast" of the climatological profile for that 15-day period. The test is

whether the RMS errors for the assimilated predictions are smaller than the other predictions.

One additional factor that must be considered when using real data is the difficulty of verifying the well-mixed layer depth predicted by the model (Figures 3a and 4b). The accuracy of the original BT observations does not permit a similar definition for verification of the model. The 0.2 method was adopted to define the MLD, and the profile was then adjusted by averaging all of the temperatures between this level and the surface. These depths determined from the 0.2 method may not be consistent with the isothermal depth in the model (Figures 4b and 5b). The isothermal depths in the model and the 0.2 method MLD from the model output profiles will be used to compare with the control data. The MLT's are changed by less than 0.2°C by these different methods of defining the MLD. An example of the control MLT compared to the model-predicted isothermal temperature during the winter regime is shown in Figure 22. Using the new MLT after the MLD was determined by the 0.2 method made virtually no change in the plotted temperatures. It is to be expected that the model isothermal layer may be considerably shallower than those found using the 0.2 method (see Figure 3). During the summer regime (Figures 23 and 24) the model-predicted isothermal depths and the 0.2 depths are quite close. The explanation for the periods when the model-predicted depths are considerably shallower than the observations is related to a warmer-than-observed bias in the temperature predictions (Figure 25). The reasons for this bias in the model will be discussed later.

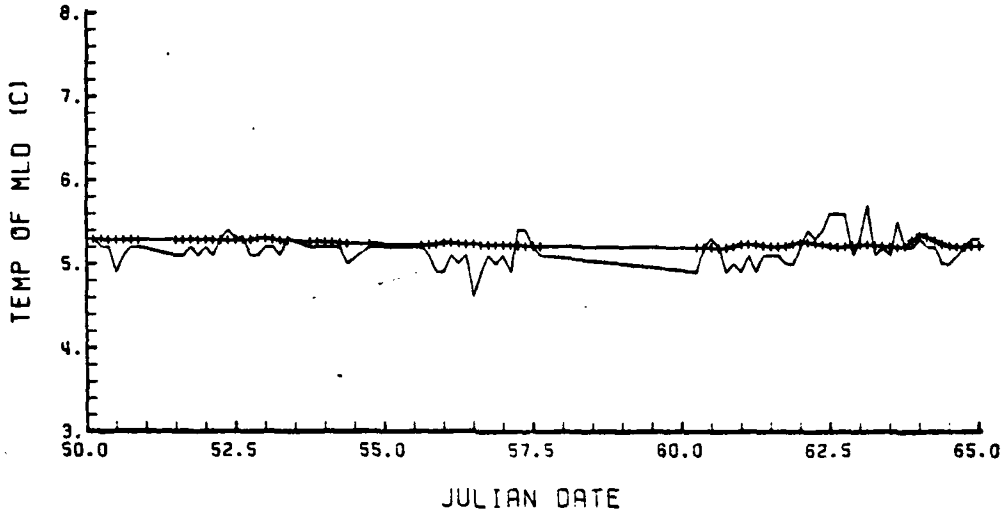

Figure 22. Winter Regime Mixed Layer Temperatures 1967, control temperatures (solid line), model output temperatures (+++).

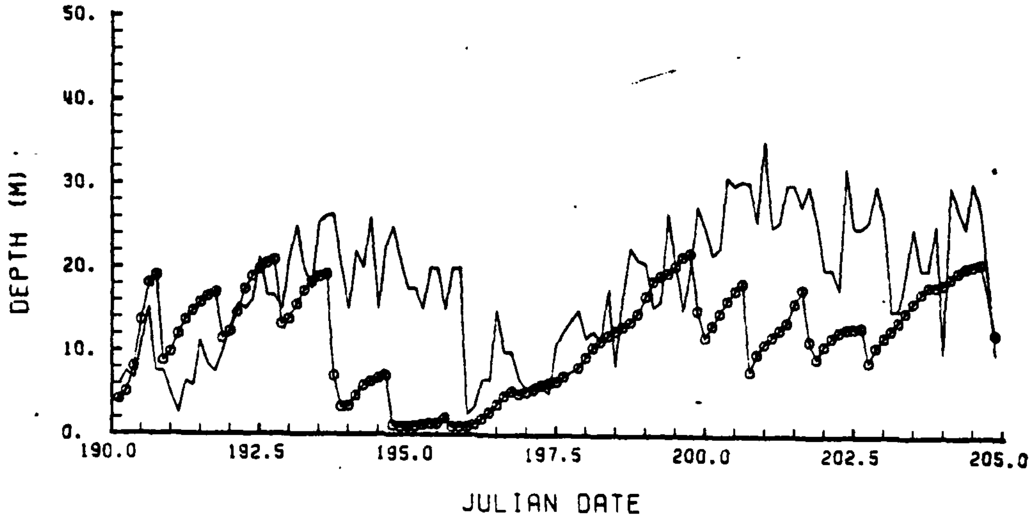

Figure 23. Summer Regime Mixed Layer Depths 1965, control MLD (solid line), model output MLD (ooo).

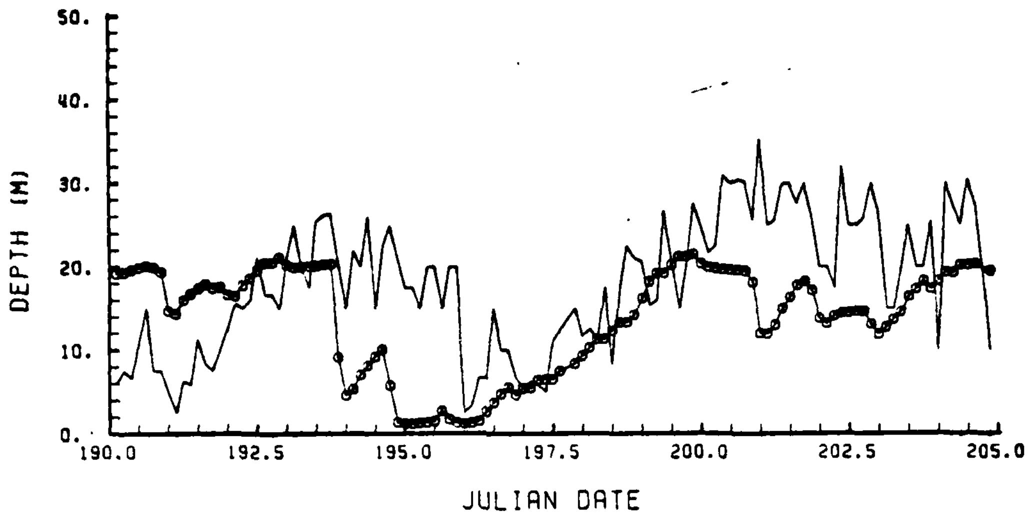

Figure 24. Summer Regime Mixed Layer Depths 1965, (solid line) same as Figure 23, (ooo) same as Figure 23, except using the 0.2 method.

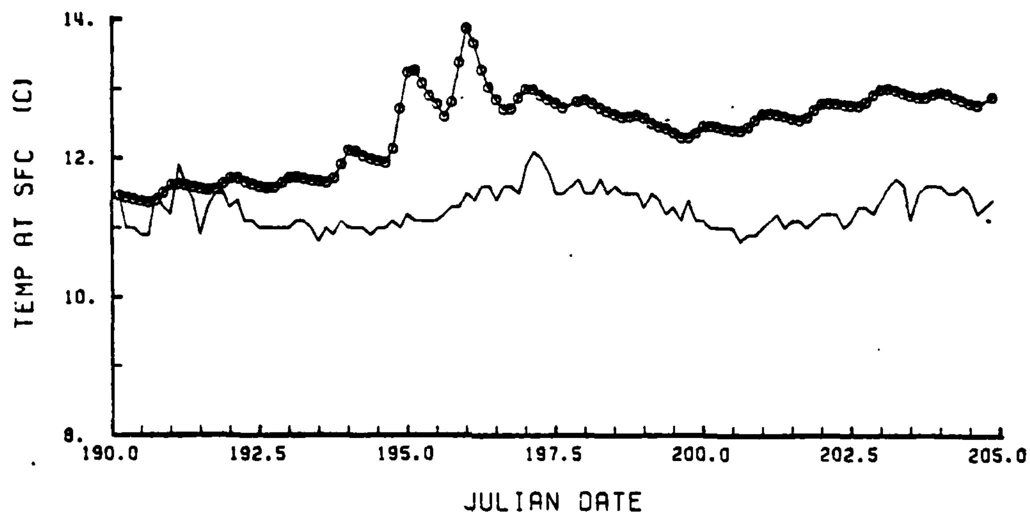

Figure 25. Summer Regime Mixed Layer Temperatures 1965, control temperatures (solid line), model output temperatures (ooo).

1. Tests Without Time-Weighting

In this case, the model-advanced profiles were simply averaged at all depths to yield a single profile. The predictions from this assimilated profile were compared with all observations during the forecast window. The set of verifications during each year occurred at varying time intervals. In the simulated verification studies, it was shown that the overall RMS results were essentially the same whether or not the same time periods were used each year. Accumulating the RMS errors by time periods over the entire 11 year study produces different numbers of verifications in each 3 hour period. Thus, there is a question of the representativeness of adjacent RMS errors. An overall RMS error for each method was obtained by averaging over all time periods. However, this does not indicate the time dependence in the errors. The 1800 GMT (0800 local) time interval seemed consistently to contain the largest sample sizes. This period was selected as a central time and adjacent periods were combined to create a single RMS value which was plotted at the central time. Two pairs of model predictions will be compared to illustrate the detail in the small time scales that was lost. In the first example (Figure 26), the errors apparently have a large variation in time, and it is not clear which method produces the better prediction. Some of the time dependence in the errors is due to the differences in sample size at adjacent times. The corresponding smoothed curves are seen in Figure 27. There is still some variability in time which is superposed on a trend toward increasingly large errors. There is still no clear indication as to which prediction is superior. In the second

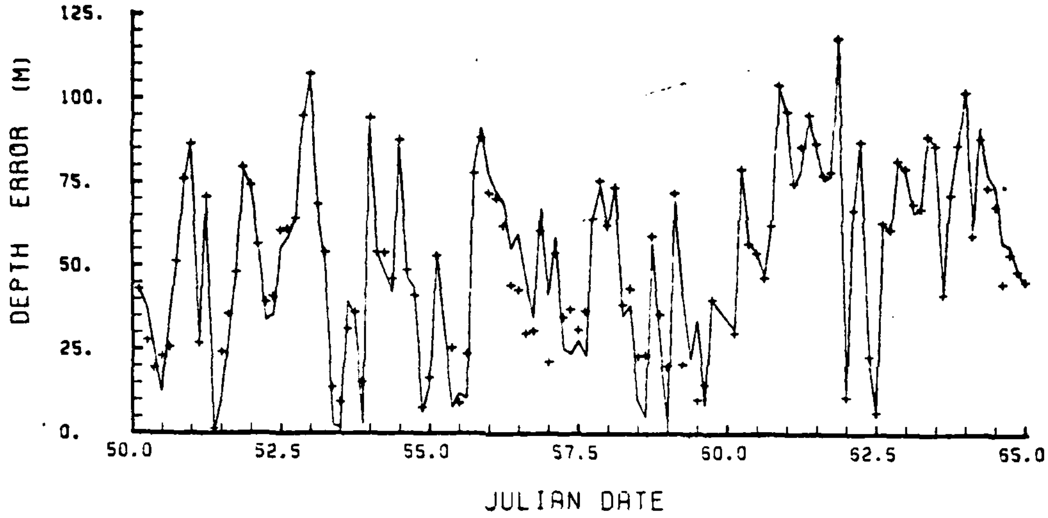

Figure 26. Winter Regime Accumulated RMS MLD Errors, assimilated prediction errors (solid line), last profile prediction errors (+++), depths were found using the isothermal layer from the model.

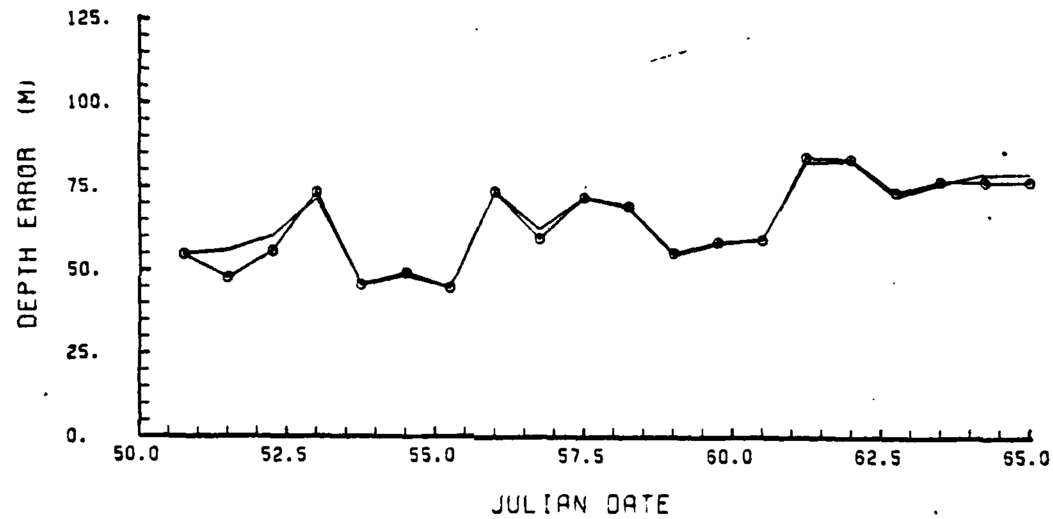

Figure 27. Winter Regime Accumulated RMS MLD Errors, (solid line) same as Figure 26, except using smoothing, (ooo) same as Figure 26, except using smoothing.

example (Figures 28 and 29), the same loss in the time dependence is apparent, but in this case, the better predictor is much more obvious. Climatology clearly is not a good profile to initialize the model in the winter if the MLT is important. Figure 29 shows the trends of the errors in the p' its, both relatively constant, whereas Figure 28 is too cluttered to reveal this trend.

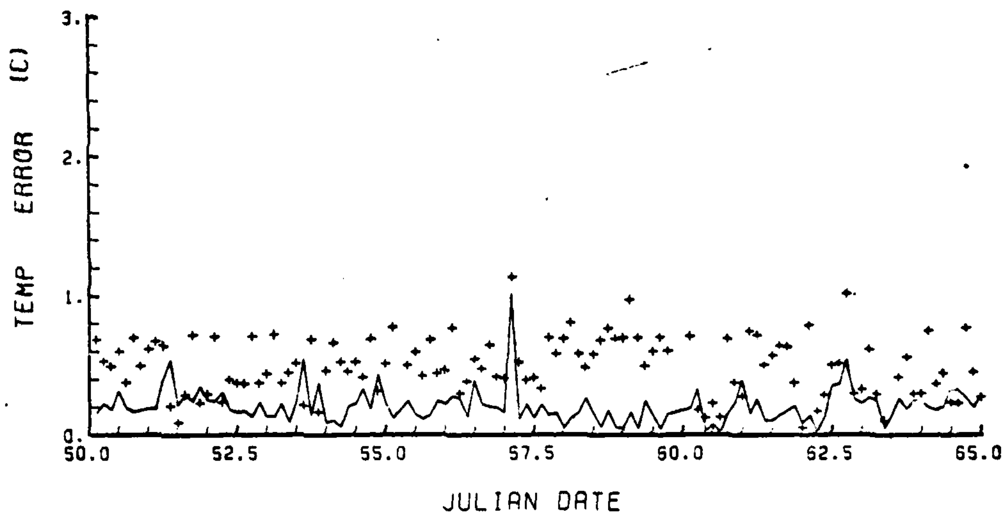

Figure 28. Winter Regime Accumulated RMS MLT Errors, assimilated prediction errors (solid line), climatology prediction errors (+++).

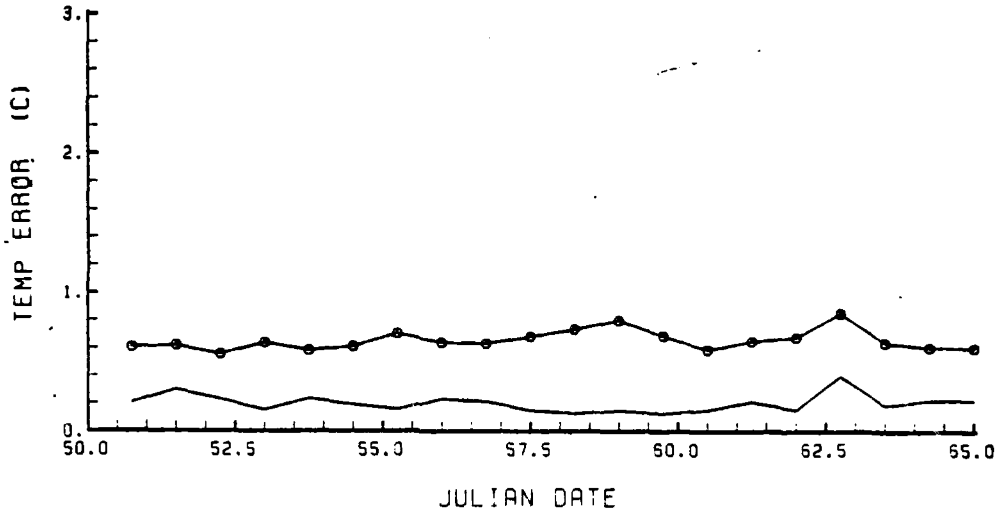

Figure 29. Winter Regime Accumulated RMS MLT Errors, (line) same as Figure 28, except using smoothing, (ooo) same as Figure 28, except using smoothing.

a. Winter Regime Results

A complete list of the winter regime error analysis is given in Table 9. Some striking results are obtained. First, the RMS MLT errors for the assimilated profiles are the smallest, although the errors for persistence and for the predictions from the last profile are nearly as good. It should also be noted that the temperature predictions starting from a climatological profile are considerably worse. The 0.68°C RMS MLT error in the total average case is actually the standard deviation of the MLT's based on the data. These RMS MLT errors are shown in Figures 30 through 32. The only clearly superior comparison is for the assimilated RMS MLT errors compared to the RMS errors from the climatological profile predictions. There is no appreciable bias in any of these RMS MLT results, which can be seen in Table 9.

TABLE 9

Total RMS error analysis during the winter without using a time-weighting for assimilation and without using the 0.2 method.
The RMS calculations are made on the predictions from the last available profile, from the assimilated profile and the climatological profile. RMS errors are also calculated on persistence and the seasons average profile.

MODEL OR NON-MODEL	GROUP	RMS h ERROR (M)	BIAS h	RMS T ERROR (C)	BIAS T
MODEL PREDICS	LAST	63.99	-45.92	0.26	-0.06
	CLIMAT	64.62	-45.73	0.67	0.01
	ASSIM	64.90	-42.25	0.25	-0.06
NON-MODEL	PERSIS	29.59	8.05	0.26	-0.03
	TOT AVG	31.93	0	0.68	0

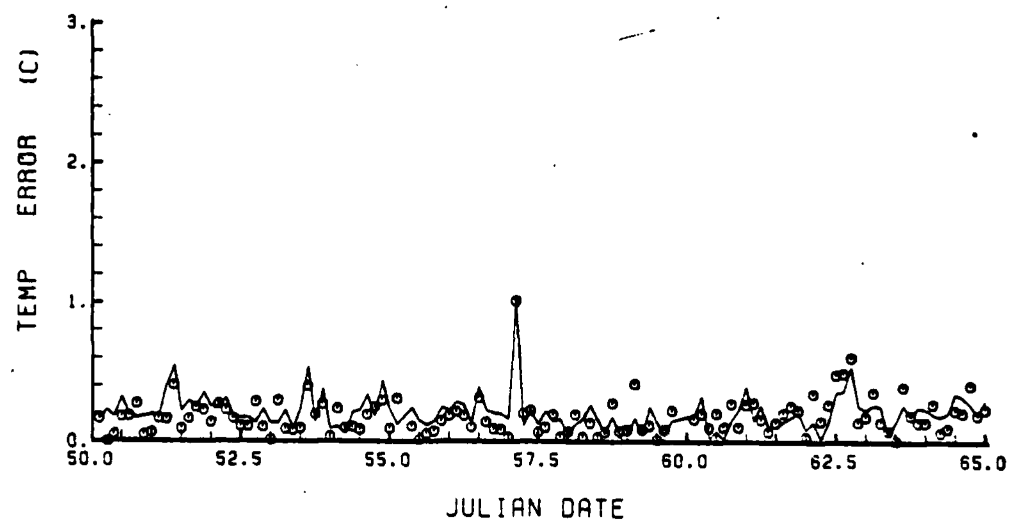

Figure 30. Winter Regime Accumulated RMS MLT Errors, assimilated prediction errors (solid line), last profile prediction errors (ooo).

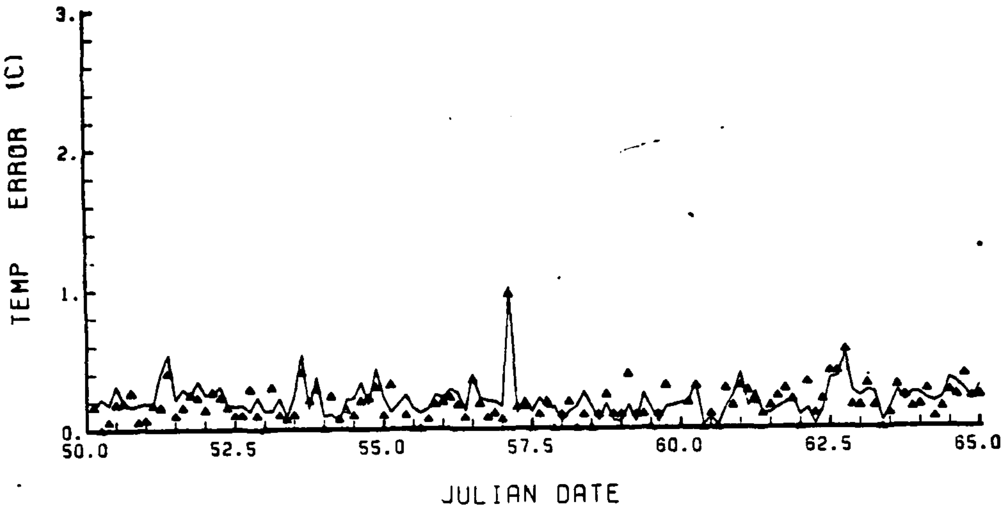

Figure 31. Winter Regime Accumulated RMS MLT Errors, (line) same as Figure 30, (ΔΔΔ) persistence errors.

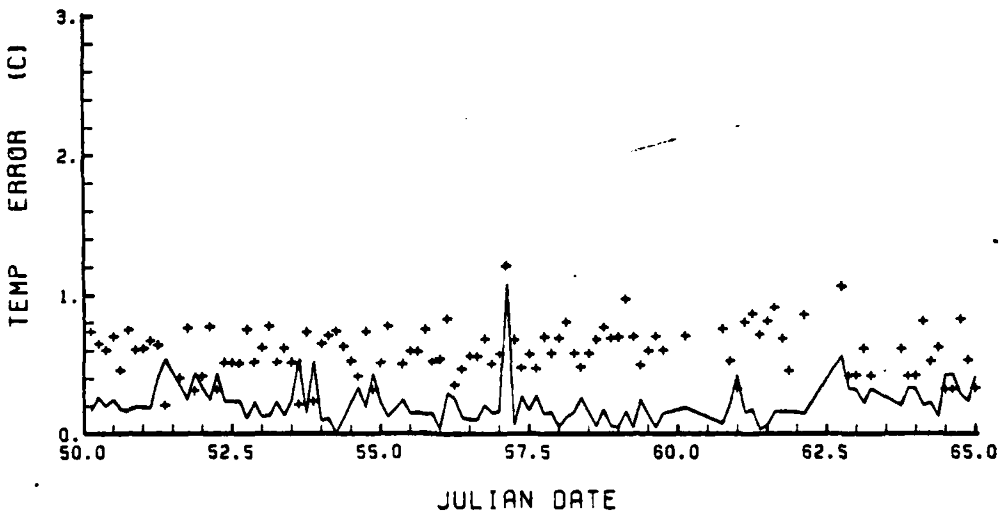

Figure 32. Winter Regime Accumulated RMS MLT Errors, (solid line) same as Figure 30, (+++) climatological profile prediction errors.

The corresponding isothermal plots (Figures 33 and 34) indicate that the model has a definite bias in layer depth predictions. As discussed earlier, this bias is related to the method of determining the MLD in the model as compared to that used with the observed data. The observed MLD remains near 150 M throughout most of the 15-day period, whereas the predictions from the assimilated (Figure 33) and last profile (Figure 34) have extended periods of apparently shallower layer depths.

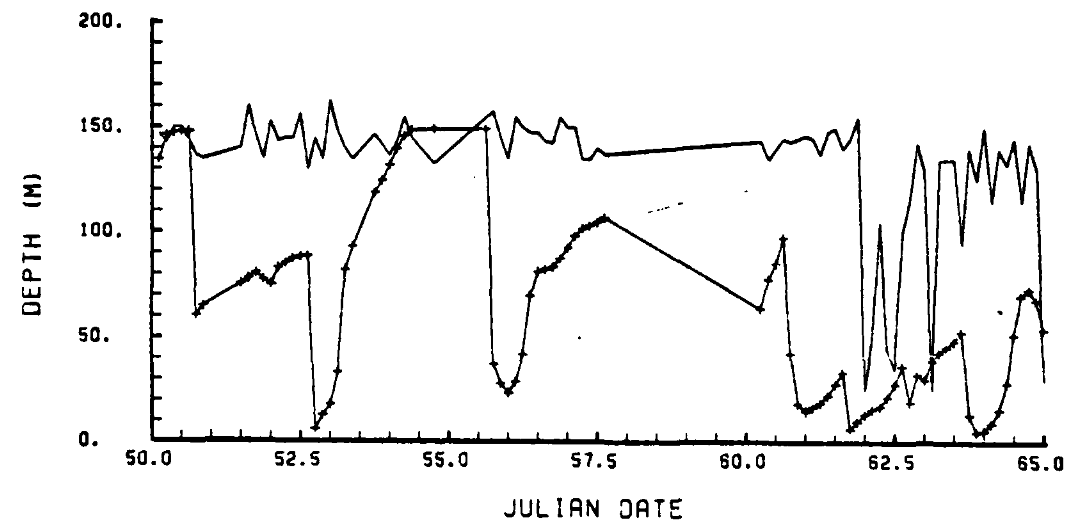

Figure 33. Winter Regime Mixed Layer Depths 1967, control depths (solid line), assimilated model predicted depths (+++).

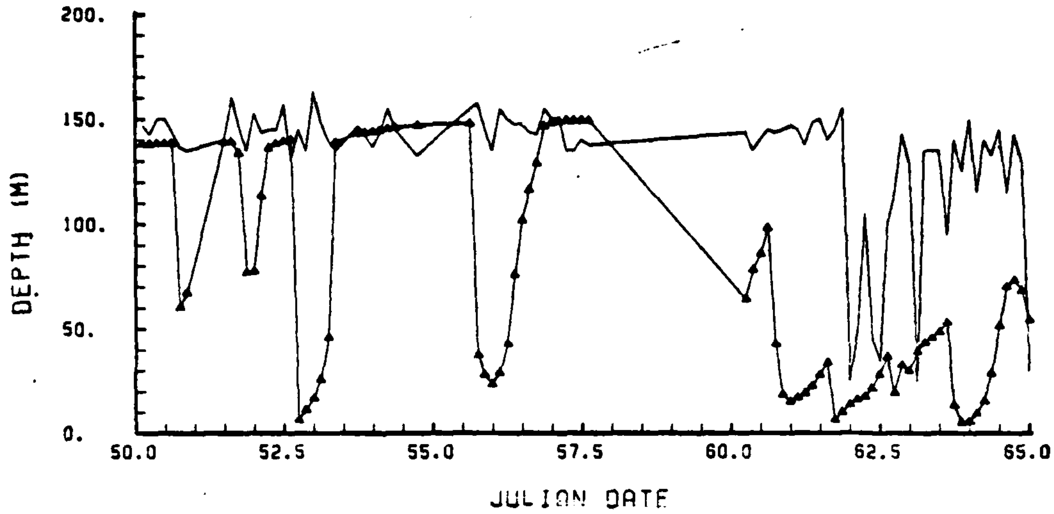

Figure 34. Winter Regime Mixed Layer Depths 1967, (solid line) same as Figure 33, (ΔΔΔ) last profile model predicted depths.

This large bias was observed in the majority of the individual predictions. When the model predicted MLD is determined using the 0.2 method, the RMS MLD errors are much smaller (Table 10). The biases are almost entirely removed in the last and climatology predictions. Comparisons of Tables 9 and 10 clearly indicate the sensitivity of the results to the method used to define the MLD. However, there was no appreciable change in the MLT prediction errors as the assimilated predictions still appear slightly better than do the other groups. The large improvement in the predictions if the 0.2 method is used to define the MLD is illustrated by the comparison of Figure 35 to Figure 36. Both predictions are improved with the largest improvement occurring in predictions from the last profile. By comparing Table 10 to Table 9, it is seen that the bias was not only reduced in the assimilated group, but it was almost completely

TABLE 10

Similar to Table 9, except using the 0.2 method.

MODEL OR NON-MODEL	GROUP	RMS h ERROR (M)	BIAS h	RMS T ERROR (C)	BIAS T
MODEL PREDICS	LAST	26.12	1.88	0.27	-0.08
	CLIMAT	30.33	4.60	0.67	-0.01
	ASSIM	35.11	23.12	0.26	-0.07
NON-MODEL	PERSIS	29.59	8.05	0.26	-0.03
	TOT AVG	31.93	0	0.68	0

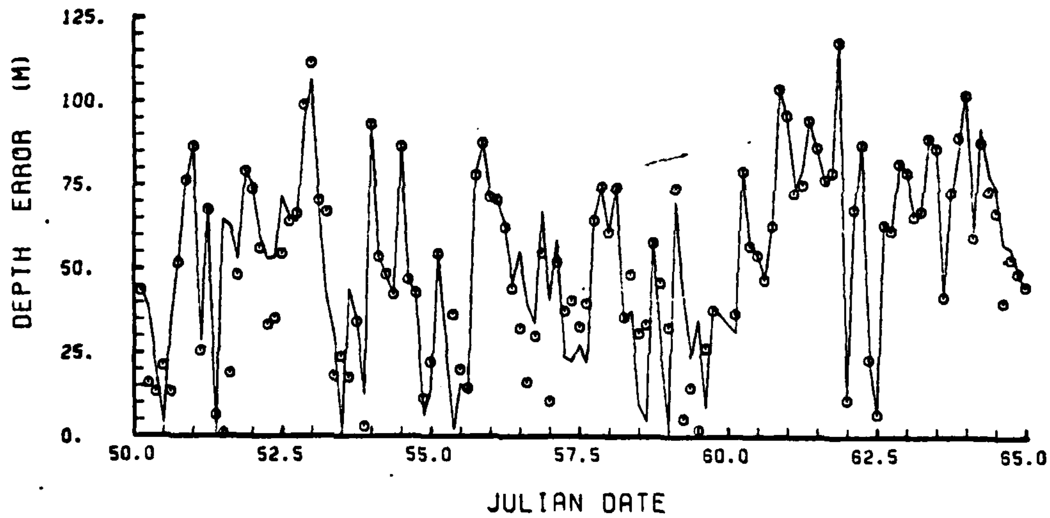

Figure 35. Winter Regime Accumulated RMS MLD Errors, assimilated model prediction errors (solid line), last profile model prediction errors (ooo).

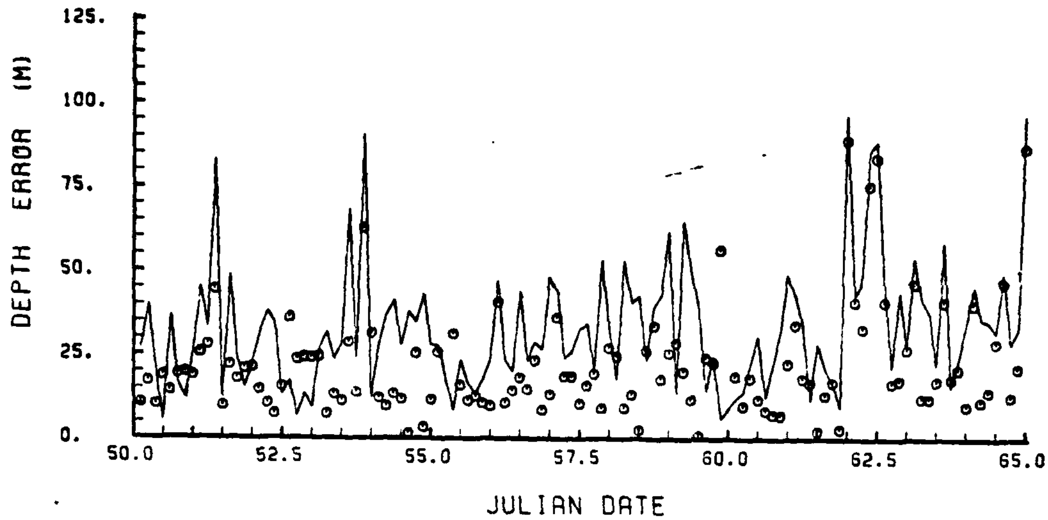

Figure 36. Winter Regime Accumulated RMS MLD Errors, (solid line) same as Figure 35, except using the 0.2 method, (ooo) same as Figure 35, except using the 0.2 method.

reversed. These preliminary results would indicate that using the last profile to initialize the model, and using the 0.2 method to calculate the MLD, results in a better prediction than any of the other methods that were tested.

Returning to Figures 4 and 5, one sees that even though the 0.2 method does indeed reduce the RMS MLD errors and the biases, the representativeness of the model to the control may be altered. By using the 0.2 method during days 50 through 62, the control MLD is well represented. During these same days, the model MLD does not resemble the control MLD at all. In the last 2 days of the period, there appears to be a change in forcing conditions as the control MLD starts to fluctuate noticeably. Here the model reacts in a similar manner while the 0.2 method determined MLD scarcely responds at all.

b. Summer Regime Results

Similar RMS error studies were made for the summer regime as was done for the winter regime. Table 11 summarizes the overall RMS errors for the summer predictions. The model predicted isothermal depths are compared to the observed control depths in this table, whereas the 0.2 method results are presented in Table 12.

TABLE 11

Similar to Table 9, except in the summer.

MODEL OR NON-MODEL	GROUP	RMS h ERROR (M)	BIAS h	RMS T ERROR (C)	BIAS T
MODEL PREDICS	LAST	11.83	-8.28	0.64	0.36
	CLIMAT	11.72	-7.88	1.56	1.22
	ASSIM	11.74	-8.59	0.82	0.65
NON-MODEL	PERSIS	12.53	0.14	0.94	-0.76
	TOT AVG	8.10	0	0.91	0

TABLE 12

Similar to Table 10, except for the summer regime.

MODEL OR NON-MODEL	GROUP	RMS h ERROR (M)	BIAS h	RMS T ERROR (C)	BIAS T
MODEL PREDICS	LAST	10.37	-6.98	0.64	0.35
	CLIMAT	10.11	-5.87	1.55	1.20
	ASSIM	10.39	-7.37	0.82	0.64
NON-MODEL	PERSIS	12.53	-0.14	0.94	-0.76
	TOT AVG	8.10	0	0.91	0

None of the predictions are clearly superior in terms of depth errors, as the summer period depths are generally small. There appears to be a fairly significant bias in all of the model MLT predictions. This bias may be attributable to under-mixing by the model and could be corrected by an improved tuning of the entrainment "constant". The model-predicted warm and shallow bias also might be due to over specification of the net downward surface heat flux, or to selection of too large of a extinction coefficient for solar radiation. Figure 25 is a typical example of the observed MLT and a model prediction during the summer regime. Even in cases in which the model-predicted MLT was less than the control MLT at the start of the forecast window, the model temperatures were noticeably higher by the end of the period. The corresponding model-predicted depths in Figures 23 and 24 indicate a clear bias toward shallow depths. Using the 0.2 method to define the mixed layer depths in the summer predictions (Table 12) produced relatively smaller changes than in the winter case. The MLT predictions continue to have a warm bias and the MLD predictions continue to have a definite shallow bias, although it was slightly improved. The reduction in the MLD bias contributes to a small reduction in the RMS errors for each of the model predictions. The assimilation predictions are generally similar to the other groups, although the last profile predictions are the best, as was the case in the winter regime.

A persistence forecast for the temperature during the summer is clearly inferior to the model predictions from the last and assimilated profiles. The superiority of the predictions from the last profile again indicates that a time-weighted average may improve upon the assimilated predictions.

2. Time-Weighted Results

From the winter and summer results in the previous section, there seems to be some hope that using a time-weighted data assimilation technique will improve the prediction. The only changes that will be discussed in this section are relative to the assimilated predictions during the winter and summer. Rather than simply adding each profile at the start of the forecast window, a time-weighting technique is used to create the assimilated profile. That is, a recent profile will be given a large weight, whereas a profile from the beginning of the history window will be given very little weight.

a. Winter Regime

During the winter regime, it was apparent that the method of specifying the MLD was a very significant factor. Because the 0.2 method clearly produced better comparisons among the various model predictions and the observed control data, the remainder of this section will treat these comparisons only. Table 13 shows the time-weighted assimilation RMS errors compared to the non time-weighted RMS errors in the winter regime, both using the 0.2 method. The time-weighting did improve upon

TABLE 13

RMS errors for time-weighted assimilation profiles compared to non time-weighted results from Table 10 during the winter regime.

	RMS h ERROR (M)	BIAS h	RMS T ERROR (C)	BIAS T
NON TIME-WEIGHTED	35.11	23.12	0.26	-0.07
TIME-WEIGHTED	34.19	21.39	0.25	-0.08

the RMS errors in the above examples, but not enough to significantly alter the results. The same type and similar biases were repeated as seen in Table 13, and the magnitude of the RMS errors was reduced only slightly. This may indicate that the noise in this test was too large to seperate the rors due to the assimilation technique. The assimilation technique produces the best MLT predictions but the apparent bias invoked by the model makes it impossible to improve on the persistence for relatively short time scale predictions of the MLD during this period.

b. Summer Regime

During the summer regime, the apparent strong bias in both MLD and MLT predictions found in the test without using a time-weighting for the assimilation continues to dominate the RMS error analysis. Table 14 shows the results of the RMS error studies using both methods to find the MLD and MLT. The results are an improvement when compared to the non time-weighted counterparts, and in fact they are now the best overall results. However, the large bias in both the MLD and MLT is still present (Figures 37 and 38). With the fairly significant improvement in

TABLE 14

Similar to Table 13, except in the summer regime. The non time-weighting results are from Table 12.

	RMS h ERROR (M)	BIAS h	RMS T ERROR (C)	BIAS T
NON TIME-WEIGHTED	10.39	-7.37	0.82	0.64
TIME-WEIGHTED	10.29	-7.19	0.75	0.55

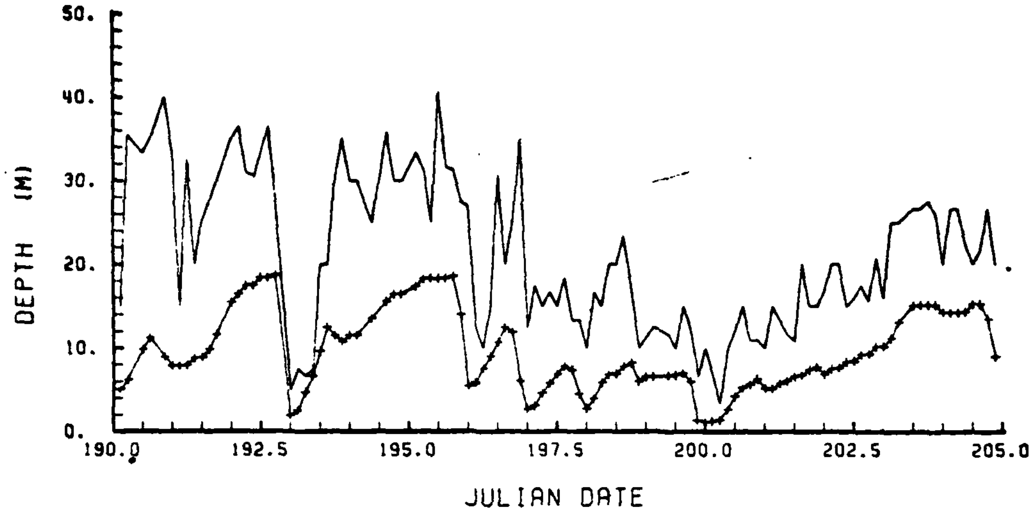

Figure 37. Summer Regime Mixed Layer Depths 1967, control depths (solid line), time-weighted assimilated depths, using the 0.2 method (+++).

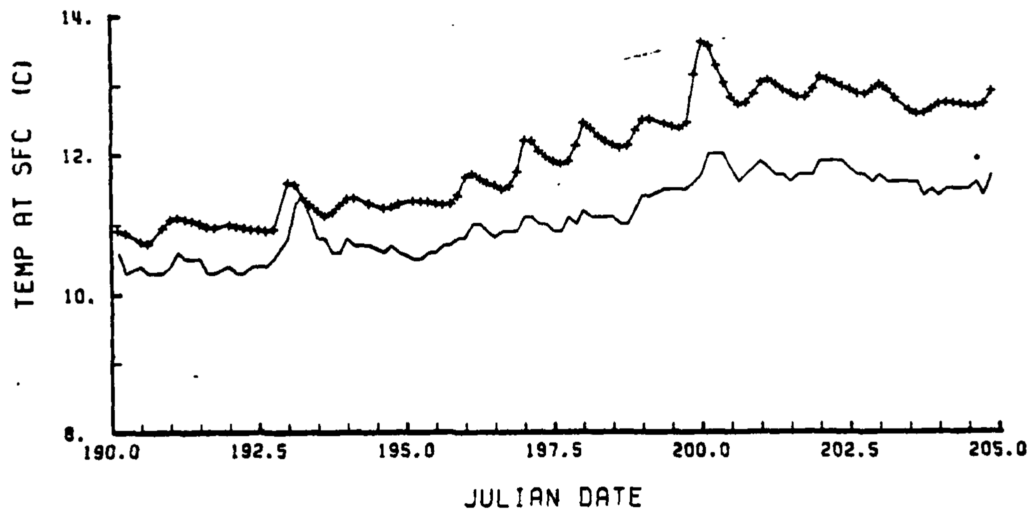

Figure 38. Summer Regime Mixed Layer Temperatures 1967, control temperatures (solid line), time-weighted assimilated temperatures, using the 0.2 method (+++).

the RMS MLT errors, if the large warm bias could be removed, then the assimilation technique would definitely be the best prediction method. Notice that the MLT is initially too high because of the warm model bias existing during the assimilation period. For this same reason, the MLD is too shallow at the beginning of the forecast window, and it remains shallow throughout this window. The biases from the model predictions must be removed before the assimilation technique using real data can produce the type of improved predictions found in the EW study with the model-generated data.

IV. CONCLUSIONS

Several conclusions can be drawn from the simulated error studies. First, the introduction of complete but noisy verification data produces a resultant error that is a vector combination of the "observational" error and the prediction errors relative to perfect verification data used in the EW study. During the winter, the noise due to observational error was not too high to obscure the differences between the predictions of the MLD. The differences between the predictions of MLT were obscured by the observational error of 0.25°C, although larger quantities of verification data improved the distinction. During the summer regime, the MLD and MLT noise introduced as observational errors were significantly large relative to the previous RMS errors in the EW study. These observational errors obscured the differences between the two predictions of MLT and MLD. The resultant RMS errors for larger and larger subsets of noisy data did approach the expected results for the complete set during both seasons. Even though these results were approached, the time dependency that may have existed in the complete and noisy case (situation 3) were lost by not doing an RMS analysis for this situation. If the errors in the verification data are not too large, then the difference between the predictions from assimilated profiles and the predictions from the last profile will be significant. It was also found that if the sample size in each time interval was different in each year the overall resultant RMS errors were not affected, but the characteristics of the time dependence changed considerably.

Phase Two of this study attempted to validate the data assimilation technique of EW with real data from OWS P. The tests involving the model predictions are greatly affected by two factors. Especially during the winter, there is an incompatibility in the model mixed layer depths and in the observations. This produces a large shallow bias in the model predictions, which increases the root mean square errors. Using the 0.2 method on the model-predicted profiles and the observations reduced this bias considerably for the winter MLD's, but not much improvement was noted during the summer. A second factor, especially during the summer, was the warm and shallow bias in the model predictions during the assimilations and during the model predictions. The origin of the warm and shallow bias may be due to the atmospheric forcing or to some model-related factor, such as the solar absorption extinction coefficient, or entrainment tuning. It was hard to improve on persistence from the last available profile during the winter regime, at least in the overall statistics over the 15 days. During the summer, the time-weighted assimilated model predictions using the 0.2 method were comparable to the other types of predictions.

If the warm and shallow bias in the model predictions can be removed, and any bias due to defining the MLD can be eliminated, the assimilated results will be improved. Then the assimilation technique using real data should prove to be a valid and useful tool that will produce useful predictions of the ocean thermal structure.

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